Momentum Strategies: Sources and Implications

By

Herbert Yan To Lam

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Abstract

This thesis consists of three studies examining the sources of momentum profits in equity market. This thesis extracts from both risk-based and behavioural based theories in searching for explanations to the existence of momentum payoffs.

Chapter 2 examines whether business cycle variables and behavioural biases can explain the profitability of momentum trading in three major European markets – France, Germany and the UK. Unlike previous studies, the chapter nests both risk-based and behavioural-based variables in a two-stage model specification in an attempt to explain momentum profits. The findings show that, although momentum profitability in European markets is unexplained by conditional asset pricing models, it is attributable to asset mispricing that systematically varies with global business conditions. In addition, behavioural variables do not appear to matter much. Thus risk factors, which are undetected thus far and are largely attributable to the business cycle, could explain the momentum payoffs in European stock markets.

Chapter 3 examines whether limits to arbitrage, overconfidence, divergence in investors' opinion, and risk factors can explain the persistence in momentum profits. The results reveal that momentum profits: (i) are driven almost entirely by loser stocks that are difficult to short; (ii) the investors' inability to short-sell loser stocks defeats the original theme of momentum trading that argues for a self-financing hedge portfolio and; (iii) the persistence in momentum profits is caused by limits to arbitrage rather than investors under-reacting to firm-specific information. Overall, momentum profits are caused by mispricing due to limits to arbitrage and overconfidence, and divergence in opinion does not play a role in overvaluation.

Chapter 4 examines the role of analyst bias and uncertainty in explaining momentum profits internationally. Momentum payoffs around the world are large and significant among higher uncertainty stocks, decrease monotonically as uncertainty decrease. Within each of the uncertainty group, the extreme winner and loser portfolios are among higher analyst bias groups. The results suggest that analysts who are concerned for their reputations report forecasts in favour with client's beliefs and hence greater analyst bias when there is greater uncertainty. The extreme winner and loser stocks continue to move to same directions reflecting investors' belief rather than the true set of information. In addition, the findings show that by forming a momentum strategy that buys low uncertainty winner and sells high uncertainty loser earns higher profits (includes most Asian countries) than the Jegadeesh-Titman (1993) momentum strategy. Thus investment strategies can be formed based on systematic behavioural biases among different groups of market participants.

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1. Introduction

1.1 Efficient market hypothesis and the momentum anomaly

An efficient market is a market in which 'prices always fully reflect available information' (Fama, 1970, p. 383). Plainly speaking, it means that the past movement or direction of the price of a stock or market cannot be used to predict its future movement. The hypothesis is that stock prices instantaneously and unbiasedly adjust to new information, which is seen as an implication of rational, utility-maximising investor behaviour in competitive markets. Fama (1970) states that for a market to be efficient, 'there are no transaction costs in trading securities, all available information is costlessly available to all market participants, and all agree on the implications of current information for the current price and distributions of future price of each security' (p.387). Expectation of future price is thus simplified by assuming that investors have homogeneous beliefs. The theory also implies a belief that stock price changes are independent of each other and have the same probability distribution, but over time maintains an upward trend. In short, the idea that stocks take a random and unpredictable path. The random walk model of asset prices is an extension of the efficient market hypothesis (EMH), as are the notions that the market cannot be consistently beaten and 'free lunches' are generally unavailable.

Theoretical challenges to the EMH question the assumed rationality of investors. Drawing on the 1970s pioneering work of cognitive psychologists Kahneman and Tversky (1974), the mid 1980s and early 1990s economists (see Black, 1986; De Long et al., 1990a) speculated that many traders (e.g. noise traders[1]) act not on information but on premonition and that the market absorbs no more rationality of calculation than it does

[1] Noise traders are investors whose beliefs and preferences conform to psychological factors rather than normative economic models.

mere noise. More recent theorising on investor behaviour has considered the nature of investor attitudes towards risk and the way investors make decisions using attention and memory more than probabilistic analysis, thus investors act irrationally in making the investment decisions.

In reality, there are a lot of imperfections in the market. First, a market is normally characterised by non-instantaneous availability and incomplete dissemination of information to all participants. This may prevent the price from incorporating the information fully and instantaneously. Secondly, there are positive information and trading costs and other institutional constraints in the market. Jensen (1968) looks at the fund managers' performance and finds that any advantage that the portfolio managers might have is consumed by fees and expenses. This has led Jensen (1978) to define an efficient market as *'A market is efficient with respect to information set θ_t if it is impossible to make economic profits by trading on the basis of information set θ_t. By economic profit, we mean the risk-adjusted returns net of all costs' (p. 96).*

Over the past twenty years there has been a growing body of literature that raises doubts as to the efficiency of the capital markets. According to this literature, a number of trading strategies exist which generate abnormal returns based solely on publicly available information. In particular, weakness from market inefficiency has been documented by Jegadeesh and Titman (1993), their trading strategy (momentum strategy) involves taking long (short) positions in firms which experience large positive (negative) abnormal returns in the previous quarter, and states that such price behaviour is consistent with positive feedback trading. In addition, Fama and French (1996) concede that momentum trading is the only CAPM-related anomaly that their three-factor model fails to explain. Subsequently, a number of behavioural models based on irrationality and psychological theories have developed in attempts to explain the momentum anomaly (see for example Barberis and Thaler, 2003). This thesis therefore proposes to examine the sources and implications of the momentum strategies.

1.2 Asset pricing model

Testing for market efficiency is difficult. It requires the market to be able to incorporate new information in prices instantly and the success of the asset pricing model in measuring the true risk factors. Flaws in asset pricing, however, cast doubts about the reliability of the existing empirical research – both the work that appears to contradict market efficiency as well as that which supports it. The continued search for appropriate risk factors to explain the apparent anomalies inform the study in chapter 2.

Chapter 2 investigates whether the apparent profitability of momentum trading can be explained by business cycle variables and behavioural characteristics in three major European markets namely France, Germany and the UK. Considering the increased debate and evidence on the role of investors' behaviour in explaining cross-sectional and time series patterns of stock returns, this chapter enhances the conditional model of Avramov and Chordia (2006) to incorporate behavioural characteristics. In addition, given the prominence of price momentum in international stock markets, this chapter applies the conditional asset pricing model of Avramov and Chordia (2006) in assessing the possible business cycle patterns within momentum profits in European markets. This offers an out of sample test of Avramov and Chordia's (2006) model in the context of momentum in stock returns in three major European markets.

The findings of chapter 2 suggest that momentum profits in Europe are largely attributable to asset mispricing that systematically varies with global business conditions. This confirms that the idiosyncratic component of stock returns does not play any prominent role in explaining momentum profits in European markets, but business cycle variables may offer a better explanation. In addition, the results of the Avramov and

Chordia (2006) model that incorporate behavioural variables display a mixed role for behavioural variables across the countries, illustrating that investors' behaviours are less likely to be correlated with the business cycle and are unlikely to explain momentum profits. Moreover, the inclusion of behavioural variables does not affect the notion that momentum patterns are risk-based. Overall, the findings of chapter 2 suggest that the profitability of momentum strategies in Europe could be explained by risk factors, which are undetected thus far and are largely attributable to the business cycle.

1.3 No free lunch and limits to arbitrage

In an efficient market, 'prices are right' in that they are set by rational agents. And there is 'no free lunch', which means that no investment strategy can earn excess risk-adjusted returns, or average returns greater than are warranted for its risk. Barberis and Thaler (2003) suggest that even when an asset is wildly mispriced, strategies designed to correct the mispricing can be very risky (e.g. fundamental risk), rendering them unattractive. As a result, behavioural finance states that 'prices are not right'. However, prices distant from fundamental value do not necessarily mean that there are any excess risk-adjusted returns for the taking. Not only arbitrageurs find that the strategies are risky but every investor does as well. Even if there is no fundamental risk, there is risk associated with unpredictable sentiment.

From the theoretical point of view, there are reasons to believe that arbitrage is a risky process and therefore that it is only of limited effectiveness. Also, there is some empirical evidence of limited arbitrage provided, such as twin shares, closed-end fund, ADR's and index inclusion[2]. In addition, De Long et al. (1990a) show that noise trader risk is powerful enough that, even with this single form of risk, arbitrage can sometimes be limited. As a result, the theory of limited arbitrage could cause deviations from

[2] For surveys of the vast literature on capital market inefficiencies, including discussions of the reasons why mispricings are not easily arbitraged away, see Shleifer (2000) and Barberis and Thaler (2003).

fundamental value and contradict the assumption of EMH. The notions of 'no free lunch' and limited arbitrage underlie chapter 3 which examines whether momentum profits are caused by limits to arbitrage and overconfidence, and whether momentum profits could be exploitable.

Using a unique sample of data on UK ownership distribution from the PricewaterhouseCoopers Corporate Register published by Hemmington-Scott to capture short selling activities, Chapter 3 finds that momentum profits come from loser stocks. There is strong evidence of a positive relationship between short-sale constraints and the magnitude of momentum profits. The known risk factors cannot explain the momentum profits. However, the results are inconsistent with Miller's (1977) view that stocks that are subject to both short-sale constraints and high divergence in opinion are initially overvalued and generate low subsequent returns. This thesis finds that momentum profits are linked with short sale constraints but not with divergence in opinion. On the other hand, excessive optimism together with self attribution bias leading to overvaluation and therefore low subsequent returns explains the momentum profits. Overall, momentum profits are caused by mispricing due to limits to arbitrage and overconfidence, and momentum profits would hardly be exploitable due to the absence of short sales.

1.4 Behavioural explanations

The consistent profitability of the momentum strategy poses a strong challenge to the efficient market hypothesis, and considerable numbers of papers have explored some behavioural explanations for the strategy's existence. Jegadeesh and Titman (1993) claim that the positive stock return autocorrelation is driven by either underreaction or a delayed overreaction that can be attributed to what DeLong et al. (1990b) called positive feedback trading. As investors persistently and irrationally under-react to firm specific information, rational investors can profit from their irrational counterparts. Daniel et al.

(1998) and Hong and Stein (1999), each employing different behavioural or cognitive biases, suggest that over-reaction is the source of momentum profits. Barberis et al (BSV, 1998) and Zhang (2006) suggest that investors under-react to new information and stock prices continue to move in the same direction.

Chapter 4 attempts to propose a new behavioural explanation for the profitability of momentum strategies based on global data. Using a sample of 22033 stocks covering 41 countries over the periods from 1983 to 2002 for the US, and from 1987 to 2002 for the rest of the world. Chapter 4 finds that momentum payoffs around the world are large and significant among higher uncertainty stocks, decreasing monotonically as uncertainty decreases. Within each of the uncertainty groups, the extreme winner and loser portfolios are among the higher analyst bias groups. The results suggest that analysts who are concerned for their reputations report forecasts in accordance with clients' beliefs and hence greater analyst bias when there is greater uncertainty. The extreme winner and loser stocks continue to move in the same directions reflecting investors' beliefs rather than the true set of information. In addition, the findings show that by forming a momentum strategy that buys low uncertainty winners and sells high uncertainty losers investors earn higher profits (including most Asian countries) than under the Jegadeesh-Titman momentum strategy. Thus investment strategies can be formed based on systematic behavioural bias among different groups of market participants.

2. Profitability of momentum strategies in international markets: The role of business cycle variables and behavioural biases

2.1 Introduction

Jegadeesh and Titman (1993) report that a trading strategy that buys stocks that have recently performed well and shorts stocks that have recently performed poorly can generate significant positive returns. The successes of momentum trading strategies have challenged the rational expectations based predictions of modern finance theory as they violate the central theme of the efficient market hypothesis that past stock returns cannot be used in generating excess returns. Fama and French (1996) concede that momentum trading is the only CAPM-related anomaly that their three-factor model fails to explain. The profitability of momentum strategy is not limited to the US market; it has been evident in many markets around the world. For instance, Rouwenhorst (1998) examined twelve European countries from 1980 to 1995 and reports that taking long positions on winner portfolios and short positions on loser portfolios can generate a risk-adjusted return of more than 1% per month[3].

While the existence of momentum in stock returns is well documented, there is considerable controversy in the literature about the sources and the interpretations of the apparent profits. In particular, both risk and investor behaviour based explanations have been put forward. Regarding risk-based explanations, Grundy and Martin (2001) use the Fama and French three-factor model to adjust for cross-sectional differences in risk. They report that neither the cross-sectional variability in required returns nor the reward for bearing industry risk can fully explain momentum profits. Apparently at odds with this view, Chordia and Shivakumar (2002) find that momentum is driven by business cycle variables[4]. By applying a predictive regression framework, they identified a possible path for rational pricing theories to explain momentum profits. They show that the profitability

[3] The literature on the profitability of momentum trading is very extensive. Interested readers are advised to consult Swinkels (2004) for an excellent survey of the literature on this issue.

[4] The motivation of using the business cycle/macroeconomic variables to explain momentum profits is because previous studies such as Fama and French (1989) and Pontiff and Schall (1998) show that macroeconomic variables can successfully predict market returns, therefore could be applied to firm-level momentum.

of momentum strategies is due to the cross-sectional differences in expected returns and that momentum profits are only a compensation for bearing business cycle risk. However, Cooper et al. (2004) show that the predictive regression model of Chordia and Shivakumar (2002) cannot explain momentum profits following up-turns, even though it to some extent explains the cross section of stock returns following down-turns. Therefore, the ability of the business cycle to explain momentum profits remains unresolved. On the other hand, Cooper et al. (2004) find that momentum strategies are only profitable following period of UP market states, suggesting that the results are in line with the overreaction models of Daniel et al. (1998) and Hong and Stein (1999). According to Daniel et al. (1998), the level of overconfidence increase during up-markets will produce stronger over-reaction and therefore higher medium term momentum. Meanwhile, Hong and Stein (1999) suggest that due to the drop in risk aversion during wealth increase leads to stronger delayed overreaction, therefore greater momentum. Nevertheless, some behavioural finance theorists argue that the persistence in momentum profits may be attributed to the disposition effect, implying that investors are reluctant to sell losers and eager to dispose of winners (see Shefrin and Statman, 1985). Ranguelova (2001) points out that the disposition effect operates entirely through the selling behaviour of individual investors. As a result, momentum profits could exist in both UP and DOWN market states.

Although the findings of Grundy and Martin (2001) and Chordia and Shivakumar (2002) are apparently at odds, they are not inconsistent. In particular, Avramov (2004) shows that return predictability based on explanatory variables in predictive regressions can be attributable to either predictable asset mispricing or predictable risk premiums or both. As a result, the findings of Chordia and Shivakumar (2002) do not necessarily trace momentum profitability to risk based asset-pricing models. Avramov and Chordia (2006) overcome the limitations of Chordia and Shivakumar's (2002) model and extend the literature further by examining "... the empirical performance of conditional asset pricing models in a framework where factor loadings may vary with firm specific market capitalization and the book-to-market ratio as well as with business cycle related variables." (p. 1). Based on such a model they report a business cycle pattern to momentum profits and conclude that the profitability of momentum strategies is attributable to a systematic rather than idiosyncratic component of stock returns. Overall, they show that momentum profit in the US is entirely captured by asset mispricing that varies with macroeconomic variables[5]

The primary motivation of this chapter is twofold. First, considering the increased debate and evidence on the role of investors' behaviour in explaining cross-sectional and time series patterns of stock returns, this chapter enhances the conditional model of Avramov and Chordia (2006) to incorporate behavioural characteristics. In addition, this chapter starts by investigating whether momentum profits in European stock markets can be predicted using the business cycle variables in the framework of Chordia and Shivakumar (2002).

Second, given the prominence of price momentum in international stock markets, this chapter applies the conditional asset pricing model of Avramov and Chordia (2006) in assessing the possible business cycle patterns within momentum profits in European markets. This offers an out of sample test of Avramov and Chordia's (2006) model in the context of momentum in stock returns in three major European markets - France, Germany and the UK.

Overall, this chapter makes two major contributions. First, it examines conditional pricing in European stock markets in the context of explaining momentum profitability, whereas previous work focused on US markets. Second, it nests both risk-based as well as behavioural-based variables[6] in a robust two-stage specification. The results help in bridging the gap of the unresolved issues on how risk and behavioural variables play parts in generating payoffs from momentum trading.

[5] Wu (2002) shows that it is possible to capture return momentum by incorporating conditional information (lagged macroeconomic variables and a conditional version of the Fama-French three-factor) into asset pricing. Although he shows that risk is not linear when cross-sectional restrictions are imposed, the risk exposures remain unidentified. Unlike Wu (2002), Avramov and Chordia (2006) investigate individual stocks, rather than portfolios, and allow alpha to vary with business conditions. The variation in alpha captures momentum profitability.

[6] The behavioural variables used in the chapter include the dispersion in analysts' earnings per share (EPS) forecasts, the mean forecast error and the analyst coverage. These are in essence firm-specific variables.

In summary, this chapter demonstrates that momentum strategies are profitable in all three major European markets. An application of the predictive regression framework of Chordia and Shivakumar (2002) cannot capture momentum profits. However, when the conditional asset pricing model of Avramov and Chordia (2006) is applied, momentum profits are found to be related to model mispricing that varies with business cycle variables. This confirms that there are business cycle patterns within momentum profits, but not all risk factors that are responsible for momentum in stock returns are identified. These findings are consistent with the evidence reported by Avramov and Chordia (2006) for the US markets. Moreover, the performance of the Avramov-Chordia model in European markets is robust to the inclusion of behavioural variables. The role of behavioural variables is mixed across countries, illustrating that such variables are less likely to be correlated to the business cycle and unlikely to be able to explain momentum profits. Therefore, it would be premature to reject the ability of rational expectations based asset pricing models to explain momentum in stock returns.

The rest of the chapter is structured as follows. The next section explains the models and section 3 describes the sample. Section 4 discusses the profitability of momentum trading strategies and the possible sources of momentum profits. Section 5 concludes the chapter.

2.2 Momentum strategies and business cycle

2.2.1 Price momentum strategies

To offer comparability of the results with the evidence reported in the literature, this chapter starts by examining the presence of price momentum in the sample countries. The chapter follows Jegadeesh and Titman (1993) in constructing the momentum strategies. One month is skipped between the formation and holding periods to avoid capturing any short-term price reversals or bid-ask bounce effects detected in previous studies (Jegadeesh and Titman, 1995). Portfolios are formed (rebalanced) each month. Equally weighted holding period returns are estimated for all deciles and for winner minus loser (W – L) portfolios. Overlapping portfolios are constructed to increase the power of the tests (see, Jegadeesh and Titman, 1993, for an explanation). The Newey and West (1987) procedure is used to control for heteroscedasticity and autocorrelation in standard errors.

2.2.2 Business cycle model

Chordia and Shivakumar (2002) show that business cycle variables can explain momentum profits in the US. Therefore, the chapter starts by employing a business cycle model similar to that of Chordia and Shivakumar (2002) to investigate whether momentum profits in Europe are explained by a set of such variables. The 3-month Treasury bill yield (*YLD*), the value-weighted market dividend yield (*DIV*), the default risk premium (*DEF*) and the term spread (*TERM*) are included in the business cycle model. Table 2.1 presents the details (definition, measurement and source) of these variables for each sample country. One-month ahead-predicted returns for each sample stock are obtained using equation (2.1) as in Chordia and Shivakumar (2002):

$$(2.1) \qquad R_{i,t} = \varphi_{i,o} + \sum_{j=1}^{4} \varphi_{i,j} BC_{j,t-1} + \varepsilon_{i,t},$$

where, $R_{i,t}$ is return (inclusive of dividends) of firm i in month t, BC is the vector of j (for j = 1 to 4) macroeconomic variables representing business cycle variables (*DIV, YLD, TERM*, and *DEF*), and $\varepsilon_{i,t}$ is the error term of stock i at time t. For each month/stock observation, the parameters of the model ($\varphi_{i,j}$, j = 0 to 4) are estimated using the previous 60 monthly returns[7]. These time-varying coefficients are used to estimate the one-month-ahead predicted return for each stock. Next, the stocks are ranked using the predicted returns and long and short positions taken accordingly. The stocks are held for 6 months from the month of portfolio formation.

[7] This chapter follows Chordia and Shivakumar (2002) to restrict the sample to stocks that have at least 24 observations in the estimation period in order to avoid spurious parameter estimates.

Table 2.1 Business cycle variables, sources and their measurement

Country	Short-term financial securities	Market Dividend Yield	Corporate Bonds	Long-term government bonds
UK	3-month Treasury bill	Dividend yield on Financial Times all Share Price Index	UK FTA Debenture and Loan Stock Redemption Yield (1977.1-1995.10) and Corporate Bond Yield (1995.11-2002.6)	U.K. Gross Redemption Yield on 20-year Gilts
Germany	3-month FIBOR	Dividend yield on Germany DS-Market constituents	Corporate bonds rate[1]	Long Term Government Bond Yield (9-10 Years Maturity)
France	Call money Rate	Dividend yield on France DS-Market constituents	Obligations private sector yield rate[2]	Government Guaranteed Bond Yield (EP)

Notes:
[1] Source: the Economist
[2] Source: Banque de France
Unless otherwise indicated, all data are obtained from Datastream

Measurement of variables:
1. YLD is measured by the rate of return on short-term financial securities.
2. DIV is measured by dividend on value-weighted broad based market index.
3. DEF (default risk premium) is measured as 'the yield on corporate bonds' less 'the yield long-term government bonds'.
4. TERM (term spread) is measured as 'the yield on long-term government bonds' less 'the yield on short-term financial securities'.

2.2.3 Business cycle, known risk factors and firm characteristics

The extant literature on the profitability of style investing shows that stock returns are dependent on firm characteristics. On the other hand, several asset pricing models (for instance, the CAPM, the Arbitrage Pricing Theory, and the Fama-French three factor model) are used in estimating the risk adjusted expected returns. If the known risk factors and business cycle variables are sufficient in explaining the variation in stock returns, the explanatory power of firm characteristics should be insignificant.

In search for an asset pricing model that can explain momentum profits, this chapter employs the two-pass cross-sectional regression based on the framework of Avramov and Chordia (2006). In their model, individual stocks are used to avoid any data-snooping biases that are frequently present in portfolio based asset pricing tests. It also avoids any loss of information that could potentially arise when stocks are sorted into portfolios. Some conditional asset pricing framework in the literature, for example Wu (2002), only condition time-varying risk on market-wide information. However, in the first-pass time series regressions of Avramov and Chordia (2006) model, the factor loadings are allowed to vary with firm characteristics (size and book-to-market ratio)[8] and business cycle conditions as in equation (2.2):

$$(2.2)\quad R_{i,t} = \alpha_{i,0} + \sum_{j=1}^{4}\alpha_{i,j}BC_{j,t-1} + \sum_{j=1}^{3}\beta_{i,j}FF_{j,t} + \sum_{j=1}^{3}\gamma_{i,j}Size_{i,t-1}FF_{j,t} + \sum_{j=1}^{3}\delta_{i,j}BM_{i,t-1}FF_{j,t} + \mu_{i,t},$$

where, $R_{i,t}$ is the return on stock i at time t, BC is the vector of business cycle variables identified earlier, FF vector represents the Fama-French three factors[9], *Size* is the natural logarithm of market capitalisation, and BM is the natural logarithm of book-to-market ratio.

In the second-pass cross-sectional regressions (equation 2.3), the returns that are adjusted for known risk factors and business cycle variables ($R^{*}_{i,t}$, obtained from equation 2.2) are regressed on firm specific variables (firm size, book-to-market ratio and past raw returns):

$$(2.3)\qquad R^{*}_{i,t} = C_0 + \sum_{j=1}^{2}\gamma_{j,t}CC_{j,i,t-1} + \sum_{m=1}^{3}\eta_{m,t}PR_{m,i,t-1} + \varepsilon_{i,t}$$

where, $R^{*}_{i,t}$ (the dependent variable) is the sum of constant and residual return ($\alpha_{i,0} + \mu_{i,t}$) of equation (2.2). $CC_{j,i,t}$ represents a vector of firm characteristic j (for $j = 1, 2$; firm size, book-to-market ratio) for security i at time t. $PR_{m,i,t}$ represents three sets of past

[8] It can also be argued that size and especially book-to-market ratio have behavioural implications.

[9] I thank Stefan Nagel for providing the UK 3-factor data. I also thank Kenneth French for making the HML data for Germany and France available. Details about the construction of the variables can be obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. I have constructed my own series of SMB for France and Germany following Fama and French (1996).

cumulative raw returns (for m = 1 to 3) over the second through third (RET2-3), fourth through sixth (RET4-6), and seventh through twelfth (RET7-12) months prior to the current month to capture the medium term momentum returns. If the predictive power of firm characteristics is represented by the known risk factors (FF) and business cycle variables (BC) in equation (2.2), the coefficients of firm characteristics ($\gamma_{j,i}$) and past cumulative returns ($\eta_{m,i}$) in equation (2.3) should be insignificant. If the cross-sections of expected returns ($\alpha_{i,0}$ + $\mu_{i,t}$ of equation 2.2) continue to experience momentum after adjusting for the business cycle variables and Fama-French three factors, the coefficients of past return variables (η_m) should be significant and positive. This would indicate the failure of the business cycle and the Fama-French 3-factor models to explain momentum profits. Statistically significant coefficients of firm specific variables (γ_j) and/or the firms' own past cumulative returns (η_m) would imply that these variables could explain the cross-section of individual stocks' business cycle and risk-adjusted returns. On the contrary, insignificant γ_j and η_m would suggest that the business cycle model, controlled for known risk factors, could capture the effects of size, book-to-market ratio, and momentum in stock returns.

2.2.4 Behavioural characteristics and stock returns

A growing body of literature on behavioural finance (see for example Barberis and Thaler, 2003) suggests that momentum in stock returns is driven by investors' behaviour and divergence in opinions. If so, the variables representing business cycle, known risk factors and firm characteristics may not be able to explain fully stock returns and momentum profits. No prior study, to my knowledge, has combined both risk factors and behavioural characteristics. This chapter contributes to the literature by examining the impact of investors' behaviour on the explanatory power of the business cycle model by revising equation (2.3) to equation (2.4) that incorporates three measures of investor behaviour:

$$(2.4) \qquad R^{*}_{i,t} = C_0 + \sum_{j=1}^{2} \gamma_{j,t} CC_{j,i,t} + \sum_{m=1}^{3} \eta_{m,t} PR_{m,i,t} + \sum_{k=1}^{3} \lambda_{k,t} BF_{k,i,t} + \varepsilon_{i,t}$$

where, $R^*_{i,t}$ (the dependent variable), $CC_{j,i,t}$ (company characteristics), and $PR_{m,i,t}$ (past cumulative raw returns) are identical to those in equation (2.3). The newly introduced vector $BF_{k,i,t}$ represents k (for $k = 1$ to 3) measures of behavioural variables. The measures of behavioural variables are: (a) the dispersion in analysts' earnings per share (EPS) forecasts (*Disp*), (b) the mean forecast error (*MFE*), and (c) the analyst coverage (*Cov*). The choice of these three behavioural factors is motivated by three behavioural theories that have been proposed to explain momentum returns. Daniel et al. (DHS, 1998) suggest investor overconfidence causes over-reaction and generates momentum, the over-reaction in prices will eventually be corrected in the long run as investors observe future news and realize their error. As a result, increased overconfidence generates momentum in the short run and reversal in the long run. This chapter employs mean forecast error as Jackson (2005) to capture analyst optimism, i.e. the level of (over)confidence.

Hong and Stein (HS, 1999) argue that private information diffuses only gradually through the marketplace leading to an initial under-reaction to news; subsequently positive serial correlation in returns attracts the attention of the momentum traders who trade actively and over-react. Eventually, prices revert back to their fundamental levels. Hong, Lim, and Stein (2000) use residual analysts' coverage as a proxy for the rate of information diffusion to test the HS model, found that the diffusion of information is lower for momentum stocks.

Barberis et al (BSV, 1998) show that investors are subject to a conservatism bias which causes them to under-react to earnings and other corporate news, causing short-run positive autocorrelation, but when they observe trends of earnings rising, the positive signal causes them to switch to over-reaction, causing long-run negative autocorrelation. In particular, investors exhibit conservatism and underreact to information that contains a high weight when adjusting their beliefs. Doukas and McKnight (2005) use dispersion in analysts' forecast to proxy the weight of information.

If momentum returns that are not explained by business cycle variables and known risk factors are related to behavioural variables then their coefficients (λ_k) will be statistically significant. In addition, a significant (non-zero) C_0 would suggest that these variables (business cycle variables, known risk factors, firm characteristics, past returns and behavioural variables) cannot fully explain company returns and hence there are other risk factors that are yet to be identified.

2.3 The sample

The sample includes all stocks listed (including subsequently delisted) in the French (Paris Bourse), German (Frankfurt Stock Exchange) and the UK (London Stock Exchange) stock markets between January 1977 and December 2002. The initial sample consists of 1,996 stocks for France, 3,063 stocks for Germany, and 4,816 stocks for the UK. The models used require at least three years' monthly share price data reducing the final sample to 1,531 stocks for France, 1,622 stocks for Germany, and 3,845 stocks for the UK.

Dispersion in analysts' EPS forecasts (Disp), mean forecast error (MFE) and analyst coverage (Cov) that are used to represent behavioural variables are obtained/derived from I/B/E/S Historical Summary file. I/B/E/S records the analysts' EPS forecasts for the sample countries from 1987 onwards only. Therefore, in the model that requires this set of data, a shorter period (1987-2002) is analysed. The dispersion in analysts' forecasts is measured by the standard deviation of forecasted EPS scaled by the stock price per share at the beginning of the month of forecast. To estimate the standard deviation of the EPS forecast, at least two analysts are required to follow the sample stock (company). The mean forecast error is the difference between the average forecasted EPS and the actual EPS of the year, deflated by the absolute value of the mean EPS forecast. The analysts' coverage is set equal to the number of analysts that supply one-year EPS forecasts. If the number of analysts following any company is not available, the coverage is set to zero.

The differential information hypothesis (Freeman, 1987) suggests that larger (smaller) companies are followed by more (fewer) analysts. It implies a high degree of correlation between the size of a firm and the intensity of its analysts' coverage. Therefore, the chapter controls for the effects of firm size on analysts' coverage and measures it by the residual ($\varepsilon_{i,t}$) of equation (2.5):

$$(2.5) \qquad \ln(AC_{i,t}) = a_0 + a_1 \ln(Size_{i,t}) + \varepsilon_{i,t}$$

where, $AC_{i,t}$ is (1+number of analysts) of firm i at month t and $Size_{i,t}$ is the market capitalization of firm i at the beginning of month t. Stock returns (R_i) are defined as the first difference of the natural log of the monthly return index (includes capital gains as well as dividend payment). Unless otherwise stated, all data are collected from Datastream. The states of the business cycle (expansionary and contractionary periods) are obtained from the website of Economic Cycle Research Institute (http://www.businesscycle.com).

2.4 The results

2.4.1 Price momentum

To examine the profitability of price momentum, the commonly used 6 x 6 strategy is used, following the methodology outlined in Jegadeesh and Titman (1993). For each month t, sample stocks in each country are grouped into deciles based on their 6-month formation-period returns. The portfolios are held for 6 months. Equally weighted returns are estimated for two extreme (winner and loser) portfolios for each month. The results (Table 2.2) show that this strategy generates (statistically significant) monthly profits of 2.10%, 1.82% and 1.44% for the UK, Germany and France respectively. Except in the case of France, a large portion of momentum profits comes from loser stocks. The apparent profitability of this strategy is consistent with the extant evidence reported in the literature. In addition, focusing on the US, previous studies show negative momentum profitability over January (for example, Jegadeesh and Titman (1993), Chordia and Shivakumar (2002) and Avramov, Chordia, Jostova and Philipov (2007)). That is, at least in US markets, January cannot trigger momentum. Thus, the chapter also examines whether January records negative payoffs in the European markets investigated. Momentum profits for January and non-January months are estimated separately. For all three countries, the average monthly momentum returns for both January and non-January months are positive and statistically significant. Although momentum payoffs in January are not negative in Europe, they are lower than in non-January months, indicating that the January effect does not 'oil the wheels' of momentum.

The chapter also examines whether the profitability of momentum strategies identified above is related to the business cycle conditions. For both expansionary and contractionary periods, stocks are grouped into deciles and returns from two extreme portfolios (winner and loser) are analysed. Table 2.2 presents momentum profits during different periods of business cycle for a 6 x 6 strategy. The estimates show that momentum profits are positive and significant during both expansionary and contractionary periods in all three countries. These estimates contradict the findings of Chordia and Shivakumar (2002) for the US that momentum profits are positive during expansionary periods and insignificant during recessions[10]. Further analysis of each market's expansionary and contractionary stages of business cycle during the sample period (not reported in the table) reveal evidence of country and business cycle stage specific variations in the profitability of momentum trading. In the UK, during expansionary (contractionary) periods momentum gains originate largely from winner (loser) portfolios. However, there were no such patterns in the cases of France and Germany. The variation in the source of momentum profits with the stages of business cycle in the UK indicates that during the expansionary (contractionary) periods most investors continue to be optimistic (pessimistic) about the stocks that are performing well (poor) in the recent past while they remain almost neutral about others. This suggests a possibility that the momentum profits are time varying and associated with the business cycle in the UK but not in France and Germany. One possible reason that the results of UK is differ from Germany and France might be due to the institutional difference of the UK, which are capital market oriented economies compared to France and Germany, which is bank oriented economies. Nevertheless, such contemporary relation between momentum profits and the stages of business cycle does not confirm the predictive ability of the business cycle model. This requires further analysis as presented in the next section.

[10] Appendix 2 shows the performance of momentum strategies for each of the business cycle in details.

Table 2.2 Payoffs (Raw returns) of Price Momentum Strategies

The average monthly returns (raw) from the 6 x 6 momentum trading strategy are reported. For each month *t*, sample stocks in each country are grouped into deciles based on their 6-month formation-period (from *t*-7 to *t*-2) returns. The portfolios are held for 6 months. Equally weighted returns of two extreme (winner and loser) portfolios for each month are estimated. The states of business cycle (expansionary and contractionary periods) are obtained from the Economic Cycle Research Institute (ECRI). The column entitled '%>0' shows the percentage of winner minus loser (W-L) cases that are positive. The *p*-values (in parenthesis of column '%>0') represent the significance level of sign test that measures whether the proportion of positive cases is significantly more than 50%. T-statistics (in parentheses) are based on the Newey-West autocorrelation consistent standard errors. *(**) denotes significance at the 5(10)% level. The sample period is January 1977 to December 2002.

Country	No. of firms	Sample	Winner (W) (T-stat)	Loser(L) (T-stat)	W – L (T-stat)	% > 0 (P-value)
		January	1.56	-0.28	1.85	76.00
			(2.59*)	(-0.40)	(4.25*)	(0.01)
		Non-January	0.87	-1.26	2.13	83.96
			(2.79*)	(-2.98*)	(6.83*)	(0.00)
UK	4816	Expansions	1.18	-0.56	1.74	80.64
			(3.34*)	(-1.24*)	(5.94*)	(0.00)
		Recessions	0.34	-2.99	3.34	95.55
			(1.11)	(-3.77*)	(5.96*)	(0.00)
		Overall	0.93	-1.17	2.10	83.28
			(3.10*)	(-2.90*)	(6.65*)	(0.00)
		January	0.81	-0.70	1.51	70.83
			(2.48*)	(-0.69)	(1.51)	(0.06)
		Non-January	0.34	-1.50	1.84	81.04
			(1.91**)	(-4.91*)	(5.85*)	(0.00)
Germany	3063	Expansions	0.68	-0.73	1.41	80.39
			(1.89**)	(-1.73**)	(4.01*)	(0.00)
		Recessions	-0.30	-3.05	2.75	79.77
			(-0.85)	(-2.65*)	(4.74*)	(0.00)
		Overall	0.38	-1.44	1.82	80.20
			(1.41)	(-2.96*)	(6.04*)	(0.00)
		January	0.82	-0.26	1.08	78.07
			(2.21*)	(-0.35)	(1.26)	(0.00)
		Non-January	0.86	-0.62	1.48	79.17
			(4.34*)	(-2.83*)	(5.33*)	(0.01)
France	1996	Expansions	0.71	-0.64	1.35	75.96
			(1.83**)	(-1.39)	(4.34*)	(0.00)
		Recessions	1.40	-0.40	1.80	86.66
			(3.07*)	(-0.64)	(4.14*)	(0.00)
		Overall	0.85	-0.59	1.44	78.16
			(2.81*)	(-1.63)	(5.48*)	(0.00)

2.4.2 The role of predicted and stock-specific returns in momentum

Chordia and Shivakumar (2002) argue that momentum in individual stock returns is related to business cycle risk in the economy. If their model holds for the sample countries and the business cycle can explain momentum profits, the holding period returns not explained by the business cycle model should not be significantly different from zero. To examine this proposition, momentum portfolios are formed on raw returns. However, the holding period returns are adjusted for the one month ahead predicted return obtained from the business cycle model (equation 2.1)[11]. The unexplained portion of the returns is defined as the intercept plus the residual (i.e. $\varphi_{i,0} + \varepsilon_{i,t}$) of equation (2.1). The intercept ($\varphi_{i,0}$) is considered not predictable as it may capture part of returns from the formation period. Predicted returns are defined as actual returns less unexplained returns. Thus, this model controls for any differences in average returns that are not related to business cycle.

Table 2.3 (panel A) reports the average holding period returns from momentum strategies that are controlled for business cycle effects. The estimates show that the profits are statistically insignificant for the UK (-0.47%) but significant for Germany (4.64%) and France (3.56%). These findings indicate that the predictive power of past returns is limited to the portion of returns that is predictable by business cycle variables for the UK, but not for France and Germany. However, it is also possible that the business cycle model simply captures the information contained in past raw returns. Hence, whether the momentum profits are attributable to the predicted part of the business cycle model or the unexplained portion of the returns is further investigated. If momentum payoff is attributable only to the predicted portion of returns, then no momentum profits should be earned by sorting stocks on the basis of their returns or on the unexplained part of returns.

To compare the profitability of momentum strategies based on the components of returns predicted by business cycle variables with the profitability of strategies based on the unexplained component of returns (or stock-specific returns), as in Grundy and Martin (2001), all stocks are ranked into quintile portfolios according to their compounded stock-specific returns (unpredicted) during the six-month formation-period. The predicted and stock-specific returns are estimated as follows. Using equation (2.1), one-period-ahead predicted returns for each stock are obtained. The unexplained (or stock-specific) return is defined as the sum of the intercept and residual of the business

[11] Appendix 3 shows the descriptive statistics of business cycle variables used in this chapter.

cycle model (i.e. $\varphi_{i,0} + \varepsilon_{i,t}$ of equation 2.1). The momentum strategy based on these stock-specific returns takes a long (short) position on the stocks with the highest (lowest) stock-specific returns during the formation period. The holding period starts one month after the end of the formation period and stocks are then held for the subsequent six-month period. Table 2.3 (panel B) presents the monthly profits from portfolios based on stock-specific (unexplained) returns. The estimates show that payoffs from this momentum trading are not significantly different from zero in any of the sample countries. However, the strategies based on predicted returns (panel C, Table 2.3) seem to generate positive and significant profits for the UK (1.10%) but not for France and Germany. These results confirm the findings of the preceding section that momentum profits can be explained by business cycle variables in the UK, but not in France and Germany.[12]

[12] A two-way dependent sort is conducted between momentum portfolios based on past raw returns and predicted returns. The effects of conditioning on the state of the market are also analysed. Both investigations, however, confirm the earlier conclusions.

Table 2.3 Payoffs from Momentum Strategy and the Business Cycle

Business-cycle adjusted holding period (6-month) returns from two extreme deciles are reported in all three panels. Portfolios in panel A are formed on raw returns (R) during the formation period. Portfolios in panel B are formed on stock-specific returns that are not predicted by business cycle. Portfolios in panel C are formed on the returns predicted by the business cycle model. Business-cycle-adjusted returns and predicted returns for each stock i (and for each month t) are computed by estimating equation (2.1):

$$(2.1) \qquad R_{i,t} = \varphi_{i,o} + \sum_{j=1}^{4} \varphi_{i,j} BC_{j,t-1} + \varepsilon_{i,t}$$

Where, BC represents business cycle variables (*DIV, YLD, TERM,* and *DEF*). The adjusted return is given by the unexplained portion of the model (i.e. $\varphi_{i,0} + \varepsilon_{i,t}$), while the predicted return (PR) is actual minus unexplained. The model parameters are estimated using data from time t-1 through t-60. The column entitled '%>0' shows the percentage of winner minus loser (W-L) cases that are positive. The p-values (in parenthesis of column '%>0') represent the significance level of the sign test that measures whether the proportion of positive cases is significantly more than 50%. T-statistics, given in parenthesis, are adjusted for autocorrelation and heteroscedasticity. *(**) denotes significance at the 5(10)% level. The sample period is January 1979 to December 2002 and firms that have a minimum of three years' data are included.

Panel A: Sort on raw returns, R; adjusted payoffs are $\varphi_{i,0} + \varepsilon_{i,t}$

Country	Winner (W) (T-stat)	Loser (L) (T-stat)	W – L (T-stat)	% > 0 (P-value)
UK	4.57 (4.41*)	5.04 (2.97*)	-0.47 (-0.23)	59.26 (0.00)
Germany	3.50 (2.41*)	-1.14 (-0.75)	4.64 (4.18*)	64.68 (0.00)
France	11.29 (7.52*)	7.34 (3.92*)	3.56 (2.60*)	56.67 (0.05)

Panel B: Sort on $\varphi_{i,0} + \varepsilon_{i,t}$; payoffs are raw returns, R.

Country	Winner (W) (T-stat)	Loser (L) (T-stat)	W – L (T-stat)	% > 0 (P-value)
UK	-0.31 (-0.70)	-0.15 (-0.47)	-0.17 (-0.74)	48.70 (0.71)
Germany	-0.01 (-0.04)	-0.23 (-0.65)	0.22 (0.86)	53.02 (0.39)
France	0.05 (0.12)	0,03 (0.07)	0.02 (0.06)	45.69 (0.21)

Panel C: Sort on predicted return, PR; payoffs are raw returns, R.

Country	Winner (W) (T-stat)	Loser (L) (T-stat)	W – L (T-stat)	% > 0 (P-value)
UK	0.20 (0.58)	-0.90 (-2.21*)	1.10 (4.40*)	72.86 (0.00)
Germany	-0.04 (-0.11)	-0.16 (-0.49)	0.12 (0.49)	56.47 (0.06)
France	0.17 (0.44)	-0.12 (-0.35)	0.29 (1.01)	59.05 (0.01)

2.4.3 *The effects of conditioning on the state of the market*

A recent paper by Cooper *et al.* (2002) documents that momentum strategies are significantly influenced by market conditions, given that profits of momentum strategies are substantially higher when the market is bullish. Additionally, they illustrate that using the macroeconomic model suggested by Chordia and Shivakumar (2002) fails to explain the asymmetries in the momentum profits. Thus, the aim of this section is to investigate how the state of the market affects the profitability of momentum strategies in the sample countries.

For the reported results, the equally-weighted returns of all securities listed on the London Stock Exchange for the UK, Frankfurt Stock Exchange for Germany and the French Stock Market over the 36 months prior to the beginning of the strategy's holding period have been employed. If the market's three-year mean return is non-negative (negative), the state of the market is defined as UP (DOWN). Consideration has also been given to a two-year and a one-year definition of the market's state.

In Panel A of Table 2.4, the average raw returns to the momentum strategy that follow three-year UP market is 1.65% in the UK, 1.29% in Germany and 1.22% in France. Besides, the performances of the momentum strategy under two-year and one year UP states are similar in all three countries. In addition, Panel B shows that profits can also be earned following DOWN market. All three DOWN states in the sample countries provide significantly positive payoffs, which are higher than UP states and associated with higher standard deviations. Contrary to the results documented by Cooper *et al.* (2002) that momentum profits exclusively follow UP periods, the results do not support the view that by conditioning on the state on the market has dramatic impact on the momentum profits.

In order to examine the robustness of the macroeconomic model (2.1) in explaining the profits of momentum strategies in the UK[13]. Table 2.5 presents two-way dependent sorts, stocks in each month are first sorted into deciles based on their predicted returns (t to $t+5$)

[13] The previous sections suggest that the macroeconomic model does not explain momentum profits in Germany and France. Thus, this chapter only focus on the performance of model in explaining the UK momentum profits.

from the business cycle model (2.1), each of these deciles are then further sorted based on the raw returns in the formation period (*t-7* to *t-2*). The average monthly return to each of the 100 portfolios over the holding period (*t* to *t+5*) is reported, and separated into UP and DOWN markets at time *t-1*. Finally, the average payoffs to momentum strategy within each of the predicted return deciles are also reported.

Panel A of Table 2.5 shows that within each of the predicted return deciles, the mean returns are generally decreasing across the raw return deciles. Furthermore, the strategy that buys winners and sells losers based on raw returns is found to earn significantly negative payoffs for all ten predicted return deciles. Similar results are found in Panel B and suggest that there is no momentum profits after DOWN states.

Unlike Cooper *et al.* (2002), who documented that there are significant momentum profits after UP states within all of the predicted return deciles. Rather, the results suggest that no profits could be earned in each of the predicted return deciles, thus provide a strong belief that the macroeconomic model is capable to explain the momentum profits, there is no evidence on different perspective between UP and DOWN market in the UK.

Table 2.4 The Profitability of Momentum Strategy in UP and DOWN Market States

For each month t, all stocks in each country are allocated into deciles based on their six-month formation-period from t-7 to t-2. Stocks are equally weighted within each decile. Reported below are the strategy's monthly profits (raw return in %) during the holding period (t to t+5) that following an UP and a DOWN market. Non-negative (negative) mean equally-weighted returns of all securities listed on London Stock Exchange define UP (DOWN) markets. Three horizons are used to describe the market state: 12, 24, 36 months. 3Cases represents the number of cases of up (down) markets. S.D (W-L) represents the standard deviation of the profits. The sample period is January 1977 to June 2002. t-statistics (in parenthesis) are adjusted for autocorrelation and heteroscedasticity. * denotes significance at the 5% level.

Panel A: UP market

	One-year UP					Two-year UP					Three-year UP				
	#Cases	W	L	W – L	S.D	#Cases	W	L	W-L	S.D	#Cases	W	L	W-L	S.D
UK	182	0.84 (2.78)*	-0.77 (-2.28)*	1.62 (6.73)*	2.48	194	0.89 (3.32)*	-0.88 (-3.41)*	1.77 (9.03)*	2.42	185	0.78 (2.42)*	-0.87 (-2.86)*	1.65 (7.80)*	2.35
Germany	149	1.70 (10.06)*	0.51 (2.71)*	1.19 (5.81) *	1.42	152	1.10 (6.93)*	-0.10 (-0.48)	1.20 (4.45)*	1.74	165	1.02 (6.03)*	-0.27 (-1.19)	1.29 (4.87)*	1.85
France	177	1.87 (6.69)*	0.62 (2.64)*	1.25 (4.45)*	1.77	173	1.20 (4.32)*	-0.12 (-0.44)	1.32 (3.87)*	2.29	173	1.15 (4.18)*	0.06 (-0.22)	1.22 (3.45)*	2.18

Panel B: DOWN market

	One-year DOWN					Two-year DOWN					Three-year DOWN				
	#Cases	W	L	W – L	S.D	#Cases	W	L	W-L	S.D	#Cases	W	L	W-L	S.D
UK	106	1.04 (4.04)*	-2.00 (-3.92)*	3.05 (9.44)*	2.67	82	0.68 (2.01)*	-2.46 (-4.25)*	3.14 (7.96)*	3.12	79	0.95 (2.79)*	-2.40 (-3.55)*	3.35 (7.34)*	3.14
Germany	144	-0.99 (-3.69)*	-3.45 (-4.63)*	2.46 (4.94)*	4.13	129	-0.62 (-1.84)	-3.23 (-3.75)*	2.61 (4.72)*	4.19	104	-0.71 (-1.82)	-3.54 (-3.40)*	2.84 (4.23)*	4.53
France	116	-0.69 (-2.96)*	-2.43 (-6.38*	1.74 (4.14)*	2.93	108	-0.10 (-0.45)	-1.69 (-4.73)*	1.59 (4.14)*	2.41	96	-0.14 (-1.02)	-2.14 (-5.66)*	1.99 (5.23)*	2.53

Table 2.5 Two way dependent sorts: Ranked by Predicted Returns and then Raw Returns in UP and Down States in the UK

For each month *t*, all stocks are first sorted into deciles based on their six-month (*t* to *t*+5) cumulative predicted returns from the business cycle model. Each predicted returns decile is then further sorted into deciles based on their raw returns over the prior six months (*t*-7 to *t*-2). Non-negative (negative) mean equally-weighted returns of all securities listed on London Stock Exchange during month *t*-36 to *t*-1 define UP (DOWN) markets. The two-way dependent sorts result in 100 portfolios. All stocks are equally weighted in a portfolio. For each portfolio, the table reports the mean monthly returns (in %) over the holding period months *t* to *t*+5) following UP(DOWN) markets. The sample period is January 1979 to June 2002. *t*-statistics (in parenthesis) are adjusted for autocorrelation and heteroscedasticity. * denotes significance at the 5% level.

Panel A: Three-year UP markets

Predicted returns	Raw returns: 1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High – Low (*t*-stat)
1(Low)	-2.61	-3.22	-3.04	-3.48	-2.91	-3.08	-2.88	-3.18	-3.07	-3.50	-0.89 (-1.92)
2	-0.87	-0.89	-0.88	-1.06	-1.02	-1.16	-1.09	-1.14	-1.28	-1.83	-0.95 (-2.57)*
3	0.10	-0.38	-0.31	-0.24	-0.35	-0.40	-0.58	-0.42	-0.76	-1.22	-1.32 (-3.87)*
4	-0.06	0.18	0.00	0.21	0.13	0.11	0.07	-0.09	-0.30	-0.62	-0.56 (-1.73)
5	0.64	0.43	0.98	0.51	0.48	0.41	0.38	0.15	0.39	-0.14	-0.78 (-2.22)*
6	1.29	0.74	0.88	0.90	0.74	0.76	0.49	0.48	0.36	0.00	-1.29 (-4.05)*
7	1.54	1.27	1.20	1.03	1.16	1.13	0.90	1.15	0.91	0.09	-1.45 (-4.51)*
8	1.84	1.60	1.69	1.47	1.58	1.60	1.40	1.37	0.91	0.44	-1.40 (-4.13)*
9	2.73	2.32	2.17	2.14	2.25	1.92	1.88	1.67	1.42	1.01	-1.73 (-4.71)*
10(High)	4.20	3.42	3.21	3.15	2.72	2.83	2.96	2.56	2.09	1.49	-2.71 (-5.06)*

Panel B: Three-year DOWN markets

Predicted returns	Raw returns: 1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High – Low (*t*-stat)
1(Low)	-4.63	-5.33	-5.97	-5.72	-6.64	-5.24	-5.77	-6.09	-5.95	-6.10	-1.47 (-1.90)
2	-1.54	-2.20	-2.46	-2.50	-2.95	-2.86	-2.81	-3.24	-3.26	-2.51	-0.98 (-1.53)
3	-1.32	-1.42	-1.68	-1.56	-1.49	-1.62	-1.83	-1.44	-1.62	-2.05	-0.73 (-1.20)
4	-0.41	-0.52	-0.64	-0.72	-0.81	-0.74	-0.75	-0.85	-0.76	-0.97	-0.56 (-0.96)
5	0.33	0.09	0.31	-0.07	0.02	-0.05	-0.19	-0.10	-0.37	-0.52	-0.85 (-1.63)
6	1.15	0.56	0.36	0.51	0.50	0.65	0.24	0.21	0.29	0.15	-1.00 (-2.19)*
7	1.25	0.82	1.14	0.85	0.79	0.92	0.89	0.98	0.69	0.45	-0.80 (-1.65)
8	2.07	1.44	1.46	1.45	1.42	1.54	1.32	1.29	1.21	1.10	-0.97 (-1.83)
9	2.50	2.13	1.94	2.02	2.05	1.90	1.87	1.96	1.88	1.68	-0.82 (-1.41)
10(High)	4.59	3.64	3.20	3.52	3.25	3.42	3.29	3.44	3.41	2.73	-1.86 (-1.99)*

2.4.4 Decomposition of momentum profits

Thus far, this chapter finds that employing a macroeconomic multifactor model can explain momentum profits in the UK, while the model fails to explain the momentum profits in Germany and France. This section follows Chordia and Shivakumar (p.1009, 2002) to decompose the momentum profits to provide a robustness test for the preceding sections. This section is based on the following model:

$$(2.6) \quad r_{it} = \mu_{it} + \sum_{k=1}^{L} \beta_{ik} f_{kt} + \sum_{m=1}^{M} \theta_{im} z_{mt} + e_{it}$$

where r_{it} is the return on security i, μ_{it} is the expected return on security i conditional on the information set at time t. f_{kt} is the return on the factor mimicking portfolio k, β_{ik} is the factor loading of security i on factor k, e_{it} is the firm-specific component of return, z_{mt} represents industry portfolio returns orthogonal to the returns on the factor-mimicking portfolios, and θ_{im} is stock i's sensitivity to the return on industry m.

During construction, the K factor portfolios, the industry components, and the idiosyncratic terms are contemporaneously uncorrelated. We therefore assume

$$E(f_{lt} f_{kt-1}) = 0, \quad \text{for all } l \neq k;$$

$$E(e_{it} f_{jt-1}) = 0, \quad \text{for all } i \neq j;$$

$$E(z_{mt} z_{nt-1}) = 0, \quad \text{for all } m \neq n;$$

$$E(z_{mt} f_{kt-h}) = 0, \quad \text{for all } m, k, \text{ and } h = \pm 1;$$

$$E(e_{it} f_{kt-h}) = 0, \quad \text{for all } i, k, \text{ and } h = \pm 1;$$

$$E(e_{it} z_{mt-h}) = 0, \quad \text{for all } i, m, \text{ and } h = \pm 1;$$

where $E(e_{it}) = 0$ for all i, and $E(z_{mt}) = 0$ for all m.

Momentum strategies are formed based on the previous sections. For each month t, all stocks in each country are allocated into deciles based on their six- month formation period from t-7 to t-2. Decile portfolios are formed monthly by weighting equally all firms in that decile ranking. The position is held for the following six- month period (t to t+5). In order to obtain a profitable self- financing momentum strategy, past winner have to continue to outperform and past losers have to continue to underperform. The expected momentum profits are:

$$(2.7) \qquad E[(r_{it} - \bar{r}_t)(r_{it-1} - \bar{r}_{t-1})] > 0$$

where a bar over a variable denotes its cross-sectional average.

Based on the assumed return-generating process, the momentum profits can be decomposed as followed:

$$(2.8) \qquad E[(r_{it} - \bar{r}_t)(r_{it-1} - \bar{r}_{t-1})] = (\mu_{it} - \bar{\mu}_t)(\mu_{it-1} - \bar{\mu}_{t-1}) + \sum_{k=1}^{K}(\beta_{ik} - \bar{\beta}_k)^2 Cov(f_{kt}, f_{kt-1})$$
$$+ \sum_{m=1}^{M}(\theta_{im} - \bar{\theta}_m)^2 Cov(z_{mt}, z_{mt-1}) + Cov(e_{it}, e_{it-1})$$

Average over all N stocks, the momentum profits equal

$$(2.9) \quad \frac{1}{N}\sum_{i=1}^{N}(\mu_{it} - \bar{\mu}_t)(\mu_{it-1} - \bar{\mu}_{t-1}) + \sum_{k=1}^{L}\sigma^2_{\beta_k} Cov(f_{kt}, f_{kt-1}) + \sum_{m=1}^{M}\sigma^2_{\theta_m} Cov(z_{mt}, z_{mt-1}) +$$
$$\frac{1}{N}\sum_{i=1}^{N} Cov(e_{it}, e_{it-1})$$

where $\sigma^2_{\beta_k}$ and $\sigma^2_{\theta_m}$ are the cross-sectional variances of the portfolio loadings and the industry sensitivities, respectively.

Equation 2.9 decomposes expected momentum profits into four components. The first component, $(\mu_{it} - \bar{\mu}_t)(\mu_{it-1} - \bar{\mu}_{t-1})$, is the cross-sectional variance of expected returns. If stocks that have expected returns that are higher than the cross-sectional mean, during both portfolio formation and holding periods, this component will increase momentum profits. The second component, $\sum_{k=1}^{L}\sigma_{\beta_k}^2 Cov(f_{kt}, f_{kt-1})$, is the serial correlation in the factors. The third component, $\sum_{m=1}^{M}\sigma_{\theta_m}^2 Cov(z_{mt}, z_{mt-1})$, is the serial correlation in the industry return components. The last term, $Cov(e_{it}, e_{it-1})$, is the average serial correlation of the idiosyncratic component of returns, determined by stock price reactions to firm-specific information.

Table 2.6 reports the results of the decomposition of momentum profits. The main contribution to the UK momentum profits is due to the cross-sectional variance of expected returns (86.75%). Further, the cross-sectional variance of expected returns remains as the main contribution to the momentum profits within both winner and loser portfolios. Rather, the situation with respect to France and Germany are very different. This chapter does not find any clear contribution for the momentum strategies in Germany and France. Yet, this chapter does not find any main sources of momentum profits in the winner portfolio. Rather, the findings show that the main contribution to momentum profits in France and Germany are due to underreaction to firm-specific information from the loser portfolios. To sum up, the decomposition of momentum profits thus reinforce the previous sections that momentum profits are driven by the cross-sectional variation of expected returns in the UK, while underreaction to firm-specific information is the main source of momentum profits in France and Germany. This section also finds that the underreaction phenomenon is more pronounced for the losers than for the winners.

Table 2.6 The decomposition of momentum profits

Momentum strategies are formed in the manner described in Table 2.2. The classifications of the expansionary and contractionary periods are obtained from the Economic Cycle Research Institute (ECRI). The percentage contributions (in parenthesis) are generated by dividing σ, δ, φ, and Ω by absolute value of the expected profits, E(π).

UK	E(π)	σ	δ	φ	Ω
Winner - Loser	0.00151	**0.00131** (86.75%)	0.00009 (5.96%)	-0.00015 (-9.93%)	0.00026 (19.85%)
Winner	0.00152	**0.00150** (98.68%)	-0.00001 (-0.67%)	-0.00016 (-10.52%)	0.00019 (12.50%)
Loser	0.00162	**0.00112** (69.14%)	0.00018 (11.11%)	-0.00002 (-1.23%)	0.00034 (20.99%)
Germany	**E(π)**	**σ**	**δ**	**φ**	**Ω**
Winner - Loser	0.00057	0.00007 (12.28%)	0.00019 (33.33%)	0.00004 (7.02%)	0.00027 (47.37%)
Winner	0.00055	0.00025 (45.45%)	0.00008 (14.55%)	0.00004 (7.27%)	0.00018 (32.73%)
Loser	0.00045	-0.00010 (-22.22%)	-0.00015 (-33.33%)	0.00009 (20.00%)	**0.00061** (135.56%)
France	**E(π)**	**σ**	**δ**	**φ**	**Ω**
Winner - Loser	0.00119	0.00061 (51.26%)	0.00011 (9.24%)	-0.00015 (-12.61%)	0.00062 (52.10%)
Winner	0.00029	0.00016 (55.17%)	0.00015 (51.72%)	-0.00016 (-55.17%)	0.00014 (48.28%)
Loser	0.00150	0.00036 (24.00%)	0.00012 (8.00%)	-0.00009 (-6.00%)	**0.00111** (74.00%)

Notes:

$$E(\pi) = E[(r_{it} - \bar{r}_t)(r_{it-1} - \bar{r}_{t-1})]$$

$$\sigma = (\mu_{it} - \bar{\mu}_t)(\mu_{it-1} - \bar{\mu}_{t-1})$$

$$\delta = \sum_{k=1}^{K} (\beta_{ik} - \bar{\beta}_k)^2 Cov(f_{kt}, f_{kt-1})$$

$$\varphi = \sum_{m=1}^{M} (\theta_{im} - \bar{\theta}_m)^2 Cov(z_{mt}, z_{mt-1})$$

$$\Omega = Cov(e_{it}, e_{it-1})$$

2.4.5 Time-varying risk premia and conditional model

The results based on the linear time series predictive regression framework, discussed in previous sections, show that momentum profits can be explained by the business cycle for the UK but not for France and Germany. Although such approach accounts for time-varying expected returns, it does not allow factor loadings to vary with conditioning information. Therefore, to examine whether the predictability of the business cycle model in the UK is due to time-varying risk premia, or time varying asset pricing misspecification or both, the two-pass cross-sectional regression model of Avramov and Chordia (2006) is employed. This model allows for both risk and expected return to vary with conditioning information.

The coefficients of the two-pass cross-sectional regression model (equation 2.3) are reported in Table 2.7. Panel A shows the payoffs from the unconditional model (similar to Fama and Macbeth, 1973) where γ_{ij} and δ_{ij} (the coefficients of product terms) of equation (2.2) are restricted to zero. Panel B presents the conditional model where size and book-to-market ratio are the conditioning variables for the factor loadings. In both models (panels A and B), the coefficients of past returns (RET 2-3, RET 4-6 and RET 7-12) are negative but insignificant in most cases. Further, the cross-sectional averages of coefficients of determination ($\overline{R}^2$) in panel B are slightly lower than those in panel A indicating that the conditional model (panel B) is marginally better in explaining the impact of firm characteristics on risk-adjusted returns. The results show that when alpha varies with business cycle variables, the firm-level momentum returns have no impact on the cross-section of expected returns unrelated to business cycle. This does not suggest that momentum profit is a compensation for bearing business cycle risk, but it reflects an existence of a business cycle pattern within the profitability of momentum strategies. This evidence is consistent with the finding of Avramov and Chordia (2006) and suggests that there might be an unidentified risk factor related to the business cycle that captures the momentum in stock prices. These findings may also be interpreted in a way consistent with investors' behaviour based models. For instance, investors may under-react to good news during expansionary periods and over-react to bad news during recessions. In reality, both of these could drive price momentum. To examine whether investors' behaviour is responsible for momentum in stock prices, this section extends the model to incorporate behavioural variables (see equation 2.4).

Table 2.7 Two-pass cross-sectional regression and time varying alpha

Time-series average of individual stocks' cross-sectional OLS regression coefficient (equation 2.3) for all securities in the UK, Germany and France are reported.

$$(2.3) \qquad R^{*}_{i,t} = C_0 + \sum_{j=1}^{2} \gamma_{j,t} CC_{j,i,t-1} + \sum_{m=1}^{3} \eta_{m,t} PR_{m,i,t-1} + e_{i,t}$$

Where, $R^{*}_{i,t}$ is the unpredicted component $(\alpha_{i,0}+\mu_{i,t})$ of time series equation (2.2):

$$(2.2) \qquad R_{i,t} = \alpha_{i,0} + \sum_{j=1}^{4} \alpha_{i,j} BC_{j,t-1} + \sum_{j=1}^{3} \beta_{i,j} FF_{j,t} + \sum_{j=1}^{3} \gamma_{i,j} Size_{i,t-1} FF_{j,t} + \sum_{j=1}^{3} \delta_{i,j} BM_{i,t-1} FF_{j,t} + \mu_{i,t},$$

$CC_{j,i,t}$ is a vector of firm characteristic j (j=1,2 i.e. firm size, book-to-market ratio of security) of stock i at time t (i.e.), $PR_{m,i,t}$ are the past cumulative raw returns of stock i over the second through third (RET2-3) fourth through sixth (RET4-6), and seventh through twelfth (RET7-12) months prior to the current month t. In equation (2.2) size is the logarithm of market capitalisation, BM is the logarithm of book-to-market ratio. BC is a vector of business cycle variables ((*DIV, YLD*, *TERM*, and *DEF*) and FF is a vector representing the Fama-French three factors.

Equation (2.3) is estimated for two separate dependent variables generated by unconditional and conditional versions of equation (2.2). First, in estimating the unconditioned dependent variable γ_{ij} and δ_{ij} of equation (2.2) are set to zero. The estimates of equation (2.3) based on this dependent variable are reported in panel A. Second, to obtain the conditioned dependent variable, size and book-to-market ratio in equation (2.2) are set to be the conditioning variables for the factor loadings. The estimates of equation (2.3) based on this dependent variable are reported in panel B. $\overline{R}^2$ is the time-series average of monthly $\overline{R}^2$. *T*-statistics (reported in parenthesis) are adjusted for autocorrelation and heteroscedasticity. All coefficients are multiplied by 100. *(**) Denotes significance at the 5(10)% level.

Panel A: Dependent variable ($R^{*}_{i,t}$) is unconditional

Country	Intercept (T-stat)	SIZE (T-stat)	BM (T-stat)	RET2-3 (T-stat)	RET4-6 (T-stat)	RET7-12 (T-stat)	$\overline{R}^2$ (%)
UK	1.213 (6.58*)	-0.564 (-17.1*)	-0.860 (-10.1*)	-0.489 (-0.86)	-0.461 (-0.89)	-1.099 (-2.16*)	3.87
Germany	1.094 (4.13*)	-0.241 (-6.90*)	-1.067 (-9.19*)	2.109 (0.98)	4.390 (1.13)	-1.313 (-0.26)	4.55
France	0.568 (1.61)	-0.228 (-4.81*)	-0.765 (-7.71*)	-1.233 (-0.92)	-1.050 (-0.58)	-3.093 (-1.40)	4.89

Panel B: Dependent variable ($R^{*}_{i,t}$) is conditioned on size and book-to-market ratio

Country	Intercept (T-stat)	SIZE (T-stat)	BM (T-stat)	RET2-3 (T-stat)	RET4-6 (T-stat)	RET7-12 (T-stat)	$\overline{R}^2$ (%)
UK	1.173 (5.64*)	-0.507 (-12.6*)	-0.493 (-5.44*)	-0.342 (-0.56)	-0.586 (-1.09)	-0.819 (-1.66)	3.14
Germany	1.707 (6.92*)	-0.285 (-6.15*)	-0.791 (-7.11*)	-3.723 (-1.31)	-0.447 (-0.13)	-11.164 (-2.51*)	4.05
France	2.603 (8.33*)	-0.382 (-8.50*)	-0.292 (-3.30*)	-1.903 (-1.32)	-3.912 (-2.13*)	-6.364 (-2.30*)	4.65

The dependent variables (unconditional and conditional) of equation (2.4) are derived with and without imposing the values of $\gamma_{i,j}$ and $\delta_{i,j}$ equal to zero in equation (2.2). Panel A of Table 2.8, where the dependent variable is derived by restricting $\gamma_{i,j}$ and $\delta_{i,j}$ equal to zero (unconditional), shows that the coefficients of prior returns (RET2-3, RET4-6 and RET7-12) remain negative (significant or insignificant). The results suggest that the inclusion of behavioural characteristics in the model does not affect the notion that momentum patterns are risk-based and they are linked to business cycle.

Panel B of Table 2.8 presents the conditional model with size and book-to-market ratio being the conditioning variables for the factor loadings. The sample of panel B is also subdivided into three groups: portfolio P1 is an equally weighted portfolio of stocks in the worst performing 30%, portfolio P2 contains the middle 40%, and portfolio P3 includes the best-performing 30%. The sub-sampling allows to examine how winner and loser stocks behave individually with the business cycle. The overall results suggest that there is no significant change in the coefficients of prior returns when behavioural variables are included in the model (equation 2.4). The coefficients remain negative and, in most cases, significant. These negative and significant slopes of prior returns suggest that the conditioning information (i.e. business cycle variables and Fama-French three factors) over-explain the momentum profits. Such findings are in line with the findings of Grundy and Martin (2001) who documented that momentum strategies based on Fama-French three factors pricing errors generate more profits than based on raw returns. The role of behavioural variables is mixed across the countries examined, having relatively stronger influence in France and the UK than in Germany. Such findings illustrate that the behavioural variables are less likely to be correlated with the business cycle, and hence behavioural variables are unlikely candidates in explaining momentum profits.

The results based on sub-samples show that much of the coefficient of prior returns (negative and significant) are from portfolio 2 (P2). This suggests that the over-explanatory power by the conditioning information and risk factors concentrates on the non-momentum stocks, except for RET7-12 where, in most cases, the returns are negative and significant. This implies a reversal in conditioning information adjusted momentum profit within a year. Overall, these results confirm the chapter's earlier findings that there are indeed business cycle patterns within momentum profits, even after controlling for investors' behaviour and prior price trend.[14]

2.4.6 Industry momentum

Moskowitz and Grinblatt (1999) claim that industry effects are almost entirely responsible for the momentum effect in the US, while Grundy and Martin (2001) document that industry momentum and individual stock momentum are distinct phenomena. This section analyses the relationship between the business cycle and industry momentum profits and examine whether it is the industry returns or the component of returns predicted by macroeconomic variable that better explains individual stock momentum.

For each month *t*, all stocks are used to compute equally weighted industry returns. Table 2.9 shows the 10 industry classifications. The time series of industry returns is then used to form the winner and the loser portfolios. The winner (loser) portfolio is the equally weighted return of the top (bottom) industry with the highest (lowest) raw returns in the six-month formation-period from *t*-7 to *t*-2. The momentum profit is then computed over the holding period (*t* to *t*+5).

[14] Equation (2.2) was revised to equation (2.2') to incorporate behavioural variables.

$$(2.2')\quad R_{i,t} = \alpha_{i,0} + \sum_{j=1}^{4}\alpha_{i,j}BC_{j,t-1} + \sum_{j=1}^{3}\beta_{i,j}FF_{j,t} + \sum_{j=1}^{3}\gamma_{i,j}Size_{i,t-1}FF_{j,t} + \sum_{j=1}^{3}\delta_{i,j}BM_{i,t-1}FF_{j,t} + \lambda_1 Disp_{i,t} + \lambda_2 MFE_{i,t} + \lambda_3 Cov_{i,t} + \mu_{i,t}$$

Where, *BC* is a vector of business cycle variables, *FF* is a vector representing the Fama-French three factors, *Size* is the logarithm of market capitalisation, *BM* is the logarithm of book-to-market ratio, *Disp* is the dispersion of analysts' forecasts, *MFE* is the mean forecast error, and *Cov* is the analyst coverage. The results, however, are qualitatively similar to those reported in Table 2.7 (panel B).

Table 2.8 Two-pass cross-sectional regression, time varying alpha and behavioural variables

Equation (2.3) is estimated for two separate dependent variables generated by unconditional and conditional versions of equation (2.2) (see Table 2.7). First, in estimating the unconditioned dependent variable γ_{ij} and δ_{ij} of equation (2.2) are set to zero. The estimates of equation (2.3) based on this dependent variable are reported in panel A. Second, to obtain the conditioned dependent variable, size and book-to-market ratio in equation (2.2) are set to be the conditioning variables for the factor loadings. The estimates of equation (2.4) based on this dependent variable are reported in panel B.

$$(2.4) \qquad R^{*}_{i,t} = C_0 + \sum_{j=1}^{2} \gamma_{j,t} CC_{j,i,t} + \sum_{m=1}^{3} \eta_{m,t} PR_{m,i,t} + \sum_{k=1}^{3} \lambda_{k,t} BF_{k,i,t} + e_{i,t}$$

Where, $R^{*}_{i,t}$ is the unpredicted component ($\alpha_{i,0}+\mu_{i,t}$) of time series equation (2.2) as in Table 2.7. $CC_{j,i,t}$ is a vector of firm characteristic j (j = 1,2, i.e. firm size, book-to-market ratio of security) of stock i at time t. $PR_{m,i,t}$ are the past cumulative raw returns of stock i over the second through third (RET2-3) fourth through sixth (RET4-6), and seventh through twelfth (RET7-12) months prior to the current month t. $BF_{k,t}$ represent investors' behaviour that are measured by (a) the dispersion in analysts' EPS forecasts (*Disp*) measured by the standard deviation in EPS forecasts scaled by the stock price per share at the beginning of the forecast month; (b) mean forecast error (*MFE*) estimated as the difference between the average forecasted EPS and the actual EPS deflated by the absolute value of the mean forecasted EPS; and (c) analyst coverage (*Cov*) measured by the number of analysts providing one year ahead EPS forecasts. Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30%, portfolio P2 contains the middle 40%, and portfolio P3 includes the best-performing 30%. $\overline{R}^2$ is the time-series average of monthly $\overline{R}^2$. *T*-statistics (reported in parenthesis) are adjusted for autocorrelation and heteroscedasticity. All coefficients are multiplied by 100. *(**) Denotes significance at the 5(10)% level.

Panel A: The dependent variable ($R^{*}_{i,t}$) is unconditional

Country	Intercept (T-stat)	SIZE (T-stat)	BM (T-stat)	RET2-3 (T-stat)	RET4-6 (T-stat)	RET7-12 (T-stat)	Disp (T-stat)	MFE (T-stat)	Cov (T-stat)	$\overline{R}^2$ (%)
UK	-1.01 (-0.95)	-0.11 (-0.56)	-0.10 (-0.32)	-1.33 (-0.80)	-0.31 (-0.22)	-0.58 (-0.42)	-5.73 (-0.60)	-22.37 (-1.08)	-0.42 (-0.50)	9.85
Germany	-0.06 (-0.06)	-0.28 (-2.32*)	-1.41 (-3.27*)	-5.50 (-0.82)	-7.62 (-1.11)	-32.05 (-3.66*)	-0.58 (-1.02)	-1.67 (-5.61*)	45.80 (1.32)	13.59
France	-6.28 (-9.85*)	0.49 (4.03*)	0.32 (0.88)	-10.79 (-1.52)	-0.60 (-0.14)	-10.78 (-2.24*)	-0.23 (-0.70)	-28.34 (-1.50)	-1.35 (-0.08)	22.72

Table 2.8 continued

Panel B: The dependent variable ($R^{*}_{i,t}$) is conditioned on size and book-to-market ratio

UK

	Intercept (T-stat)	SIZE (T-stat)	BM (T-stat)	RET2-3 (T-stat)	RET4-6 (T-stat)	RET7-12 (T-stat)	Disp (T-stat)	MFE (T-stat)	Cov (T-stat)	$\bar{R}^2$ (%)
P3	8.70 (7.29*)	-0.58 (-2.83*)	-0.58 (-1.47)	-4.93 (-1.66**)	0.24 (0.08)	-17.52 (-7.03*)	-76.68 (-2.48*)	98.28 (1.04)	-1.52 (-1.15)	33.57
P2	-0.22 (-0.24)	-0.23 (-1.66**)	-0.23 (-0.88)	-5.06 (-2.41*)	-2.67 (-1.52)	-21.27 (-11.34*)	9.45 (0.62)	-1.43 (-0.09)	0.01 (0.01)	24.61
P1	-14.37 (-3.53*)	1.17 (1.34)	0.87 (0.73)	-1.01 (-0.78)	0.72 (0.23)	-16.15 (-4.45*)	181.19 (0.95)	183.45 (1.09)	-4.75 (-1.54)	31.38
Overall	-1.70 (-3.20*)	-0.03 (-0.29)	-0.62 (-4.49*)	-2.26 (-1.77**)	-1.31 (-1.25)	-1.92 (-2.21*)	-8.71 (-1.14)	19.26 (2.30*)	-1.44 (-2.49*)	5.31

Germany

	Intercept (T-stat)	SIZE (T-stat)	BM (T-stat)	RET2-3 (T-stat)	RET4-6 (T-stat)	RET7-12 (T-stat)	Disp (T-stat)	MFE (T-stat)	Cov (T-stat)	$\bar{R}^2$ (%)
P3	7.87 (6.20*)	-0.51 (-3.82*)	-1.63 (-2.76*)	-2.15 (-0.46)	10.08 (0.87)	-104.70 (-8.51*)	0.06 (0.09)	-2.73 (-4.06*)	23.39 (0.57)	31.22
P2	2.44 (1.30)	-0.40 (-3.03*)	-0.62 (-0.83)	-3.98 (-0.82)	7.48 (0.70)	-172.20 (-10.97*)	-0.27 (-0.43)	-1.66 (-3.34*)	-54.29 (-0.96)	31.52
P1	-10.78 (-2.09*)	0.39 (0.62)	-2.28 (-2.33*)	0.91 (0.10)	-4.62 (-0.39)	-104.16 (-6.94*)	0.29 (0.63)	-2.98 (-2.32*)	-9.65 (-0.87)	29.25
Overall	-0.56 (-0.71)	-0.18 (-2.17*)	-1.91 (-6.71*)	1.34 (0.33)	3.21 (0.54)	-13.26 (-1.71**)	-0.07 (-0.42)	-2.22 (-7.07*)	0.95 (0.16)	8.49

France

	Intercept (T-stat)	SIZE (T-stat)	BM (T-stat)	RET2-3 (T-stat)	RET4-6 (T-stat)	RET7-12 (T-stat)	Disp (T-stat)	MFE (T-stat)	Cov (T-stat)	$\bar{R}^2$ (%)
P3	0.38 (0.05)	0.87 (0.63)	-3.74 (-1.05)	-30.17 (-1.20)	-72.94 (-1.58)	-215.47 (-1.42)	0.62 (0.16)	-54.82 (-0.98)	62.44 (0.47)	20.90
P2	-8.92 (-1.41)	1.50 (1.72**)	-1.42 (-0.94)	-21.43 (-1.64**)	-57.96 (-2.20*)	-224.67 (-3.99*)	0.99 (0.48)	-14.96 (-0.37)	-349.36 (-1.93**)	14.34
P1	19.86 (0.98)	-2.99 (-0.94)	-3.11 (-0.64)	27.01 (0.56)	28.96 (0.34)	-52.47 (-0.25)	-20.77 (-1.91**)	56.54 (0.60	-878.68 (-1.43)	23.82
Overall	-4.03 (-4.73*)	0.33 (3.09*)	-0.77 (-4.04*)	-4.77 (-2.00*)	-2.80 (-0.84)	-10.77 (-1.81**)	-1.59 (-6.09*)	-19.33 (-4.38*)	20.85 (1.85**)	9.14

Table 2.9 Datastream's industry classifications[a]

INDC3	Definitions
BASIC	Basic Industries
CYCGD	Cyclical Consumer Goods
CYSER	Cyclical Services
GENIN	General Industries
ITECH	Information Technology
NCYCG	Non-Cyclical Consumer Goods
NCYSR	Non-Cyclical Services
RESOR	Resources
TOTLF	Financials
OTHERS	Companies without classifications

[a] Industry data were obtained from Datastream to construct the industry portfolios. Ten industries were used according to Datastream's industry classification, Datatype INDC3.

Table 2.10 (Panel A) reports the average profits to the industry momentum, in line with Moskowitz and Grinblatt (1999). The profits are significantly positive in all three countries. While the industry momentum profits are lower than the individual momentum profits in the UK and Germany, the case of France is opposite. Panel A also presents the industry momentum profits that are based on the predicted return from the business cycle in equation (2.1). The results show that momentum profits based on predicted returns are significantly positive in the UK only. This result is consistent with those of the price momentum.

In order to examine if price momentum is caused by the industry effect or if it is a separate phenomena, this section firstly investigates if industry momentum fully explains price momentum and secondly test whether the price momentum, by taking into account the industry effects, can be explained by the business cycle model. Table 2.10 (Panel B) reports the raw returns to the momentum strategy based on industry-adjusted returns. The industry-adjusted returns are calculated as the stock returns in excess of the industry returns. The results indicate that, even after adjusting for industry returns, the average momentum profits are significantly positive in all three countries. The findings thus suggest that industry momentum does not fully explain price momentum, so the two effects are in effect separate. Panel B also reports the industry-adjusted momentum profits that are based on the predicted returns obtained from the one-period-ahead forecasts of the business cycle model. The results suggest that, even after adjusting for the industry effect, the relationship between price momentum and the business cycle remains significant in the UK only.

Table2.10 Industry Momentum Strategy

The 10 industry classifications used in this study are obtained from Datastream's industry-classification (datatype INDC3). The time series of industry returns is then used to form the winner and the loser portfolios. For each month *t*, all stocks are first sorted into deciles based on their six-month (*t* to *t*+5) industry returns/industry-adjusted returns in (Panel A/Panel B). For each stock *i* and for each month *t*, the industry-adjusted returns are calculated as the stock returns in excess of the industry returns. The winner (loser) portfolio is the equally weighted return of the top (bottom) industry with the highest (lowest) raw returns in the six-month formation-period from *t*-7 to *t*-2. The momentum profit is then computed over the holding period (*t* to *t*+5). Raw payoffs indicate the strategy's raw monthly returns during the holding period, while Predicted returns show the holding period profits that sorted by predicted returns. Predicted returns are computed in the manner described in Table 2.3. The column titled '%>0' is described in the manner as Table 2.2. *t*-statistics (in parenthesis) are adjusted for autocorrelation and heteroscedasticity. *(**) Denotes significance at the 5(10)% level.

Panel A: Payoffs from a Momentum Strategy Based on Industry Returns

	Raw Payoffs				Predicted return			
	W	L	W−L	%>0	W	L	W-L	%>0
UK	0.75	-0.69	1.43	67.58	0.33	-0.40	0.73	63.85
	(2.97*)	(-1.74**)	(5.37*)	(0.00)	(1.65)	(-1.76**)	(2.57*)	(0.00)
Germany	0.10	-0.82	0.92	56.66	-0.22	1.03	0.12	56.84
	(0.38)	(-1.81)	(3.08*)	(0.03)	(-0.11)	(0.32)	(0.58)	(0.04)
France	0.95	-0.73	1.68	65.87	0.92	0.66	0.27	58.55
	(2.50*)	(-1.60)	(4.99*)	(0.00)	(2.14*)	(1.45)	(0.91)	(0.01)

Table 2.10 continued

Panel B: Payoffs from a Momentum Strategy Based on Industry-adjusted Returns								
	Raw Payoffs				Predicted return			
	W	L	W−L	%>0	W	L	W-L	%>0
UK	0.50	0.02	0.48	60.51	0.45	0.08	0.37	62.24
	(2.38*)	(0.07)	(2.09*)	(0.00)	(1.95**)	(0.45)	(2.18*)	(0.00)
Germany	0.18	-0.37	0.54	56.88	0.15	0.08	0.07	50.83
	(1.07)	(-0.87)	(2.04*)	(0.03)	(0.42)	(0.23)	(0.28)	(0.85)
France	0.68	0.07	0.61	58.54	0.20	0.59	-0.39	54.63
	(1.70)	(0.20)	(2.20*)	(0.00)	(0.45)	(0.75)	(-0.31)	(0.18)

One interesting question, which seems to be omitted in the literature, is whether industry momentum would be subsumed by price momentum? It may not be surprising to find that the industry momentum profits are being subsumed by price momentum if the observed industry momentum is a composition of the price continuation from individual stocks rather than the industry that experiences momentum. To test this conjecture, industry momentum profits are regressed on the business cycle variables including default spread (*DEF*), term spread (*TERM*), dividend yield (*DIV*) and the three month t-bill yield (*YLD*), the Fama-French three factors and price momentum. Table 2.11 (Panel A) confirms the previous section results, showing that the business cycle model fails to explain the industry momentum in Germany and France. In contrast, the intercepts are statistically insignificant in the UK indicating some explanatory power. Adding Fama-French three-factor and price momentum to the business cycle model in Panel B results show that the intercepts are statistically insignificant in all three countries. Such effect, however, is solely due to the price momentum suggesting that the observed industry momentum is actually subsumed by momentum at the individual stock level.

Table 2.11 Time series regressions of industry momentum profits on business cycle variables, Fama-French three-factor and price momentum

This table presents the coefficients of regressions of industry momentum profits (Rp) on business cycle variables in Panel A; business cycle variables, Fama-French three-factor, and price momentum in Panel B. Business cycle variables are default spread, term spread, dividend yield and the three month t-bill yield. The industry momentum is computed in the manner described in Table 2.10. $\bar{R}^2$ is the time-series average of the monthly adjusted R^2. *t*-statistics (in parenthesis) are adjusted for autocorrelation and heteroscedasticity. *(**) Denotes significance at the 5(10)% level.

Panel A: $Rp = \alpha_0 + \beta_{1\tau} DIV + \beta_{2\tau} DEF + \beta_{3\tau} TERM + \beta_{4\tau} YLD + \varepsilon_\tau$

	α_0	β_1	β_2	β_3	β_4	$\bar{R}^2$
UK	0.016 (1.21)	1.056 (2.07*)	-0.405 (-1.78**)	-1.033 (-3.89*)	-0.743 (-1.09)	0.136
Germany	0.028 (2.11*)	-0.221 (-0.60)	-0.287 (-1.38)	-0.654 (-1.88**)	4.119 (4.96*)	0.117
France	0.026 (3.41*)	0.458 (1.33)	-0.228 (-1.57)	-0.269 (-1.11)	-1.228 (-2.20*)	0.027

Panel B: $Rp = \alpha_0 + \beta_1 DIV + \beta_2 DEF + \beta_3 TERM + \beta_4 YLD + \gamma_1(R_{mt} - R_{ft}) + \gamma_2 SMB + \gamma_3 HML + \gamma_4 WML + \varepsilon_\tau$

	α_0	β_1	β_2	β_3	β_4	γ_1	γ_2	γ_3	γ_4	$\bar{R}^2$
UK	-0.007 (-0.69)	-0.012 (-0.02)	0.071 (0.35)	-0.219 (-0.86)	-0.106 (-0.22)	0.038 (1.09)	0.043 (0.95)	0.065 (0.75)	0.767 (7.03*)	0.445
Germany	-0.015 (-0.89)	-0.346 (-1.31)	0.158 (0.80)	0.079 (0.22)	1.615 (1.17)	0.057 (1.20)	0.133 (3.27*)	-0.089 (-1.74**)	1.039 (8.18*)	0.596
France	0.005 (0.47)	0.401 (0.96)	-0.189 (-0.97)	-0.059 (-0.19)	-0.793 (-1.20)	0.001 (0.02)	0.000 (0.00)	0.014 (0.25)	1.091 (4.38*)	0.369

2.4.7 Intra-industry momentum

Although the previous section finds that both price and industry momentum profits are present in all three countries, it will be interesting to see if momentum exits within each of the industries. The successful of intra-industry momentum will indicate that industry effects fail to explain price momentum. Further, it will be valuable for practitioners' interests as this provides an alternative trading strategy that involves lower transaction costs, as lesser stocks are required to form the winner/loser portfolios. To my knowledge, this chapter is the first to investigate intra-industry momentum strategies and their relationship with business cycle within the context of Europe.

Table 2.12 shows that intra-industry momentum strategies are presented in all three countries. In fact, some of the intra-industry momentum profits in the UK and Germany are even higher than industry momentum. The findings provide an alternative trading strategy suggesting that momentum profits exist within each of the industries. However, it is worth noting that as the intra-industry momentum appears to be profitable in almost every industry, it raises the question if such effect is caused by price momentum. To test this conjecture, intra-industry momentum profits are regressed on the business cycle variables including default spread (*DEF*), term spread (*TERM*), dividend yield (*DIV*) and the three month t-bill yield (*YLD*), the Fama-French three factors and price momentum. Table 2.13 reports that almost all the intercepts are statistically insignificant. Such effect, however, is contributed to the price momentum suggesting that the observed intra-industry momentum is subsumed by momentum at the individual stock level.

Table 2.12 Intra-Industry Momentum Strategies

The 10 industry classifications used in this study are obtained from Datastream's industry-classification (datatype INDC3). The winner (loser) portfolio is the equally weighted return of the top (bottom) 30% industry with the highest (lowest) raw returns in the six-month formation-period from t-7 to t-2. The momentum profit is then computed over the holding period (t to t+5). Raw payoffs indicate the strategy's raw monthly returns during the holding period, while Predicted return show the holding period profits that sorted by predicted returns. Predicted returns are computed in the manner described in Table 2.3. t-stat. are t-statistics that adjusted for autocorrelation and heteroscedasticity. *(**) Denotes significance at the 5(10)% level

		Raw Payoffs		
		W	L	W – L (t-stat.)
UK	BASIC	0.84	-0.12	0.95 (4.36*)
	CYCGD	0.60	-0.29	0.88 (3.82*)
	CYSER	1.08	-0.45	1.52 (6.74*)
	GENIN	0.62	-0.45	1.06 (4.82*)
	ITECH	1.03	-0.63	1.66 (4.49*)
	NCYCG	1.06	-0.33	1.39 (7.06*)
	NCYSR	1.21	-0.47	1.67 (4.79*)
	RESOR	0.35	-0.40	0.75 (2.51*)
	TOTLF	0.77	-0.18	0.95 (4.30*)
	OTHERS	0.16	-1.80	1.96 (5.79*)
Germany	BASIC	0.37	-0.37	0.74 (4.08*)
	CYCGD	0.41	-0.72	1.13 (5.59*)
	CYSER	0.60	-1.12	1.72 (5.73*)
	GENIN	0.26	-0.81	1.07 (4.75*)
	ITECH	-1.41	-3.30	1.89 (2.13*)
	NCYCG	0.45	-0.17	0.62 (3.69*)
	NCYSR	-0.12	-1.37	1.25 (2.91*)
	RESOR	0.42	-0.22	0.64 (3.54*)
	TOTLF	0.64	-0.01	0.65 (3.16*)
	OTHERS	-0.06	-0.87	0.81 (1.58)
France	BASIC	0.90	0.36	0.54 (2.06*)
	CYCGD	0.74	-0.51	1.25 (4.28*)
	CYSER	1.24	0.12	1.12 (4.33*)
	GENIN	0.93	-0.11	1.04 (4.27*)
	ITECH	1.14	-0.37	1.52 (3.50*)
	NCYCG	0.80	0.17	0.64 (3.07*)
	NCYSR	1.06	0.28	0.78 (2.14*)
	RESOR	0.57	-0.29	0.86 (2.29*)
	TOTLF	0.84	0.07	0.77 (3.50*)
	OTHERS	-0.13	-0.77	0.64 (1.19)

Table 2.13 Time series regressions of intra-industry momentum profits on business cycle variables, Fama-French three-factor and price momentum

This table shows the coefficients of regressions based on the following model: $Rp = \alpha_0 + \beta_1 DIV + \beta_2 DEF + \beta_3 TERM + \beta_4 YLD + \gamma_1 (R_{mt} - R_{ft}) + \gamma_2 SMB + \gamma_3 HML + \gamma_4 WML + \varepsilon_t$. The dependent variable (Rp) is the intra-industry momentum profits. Business cycle variables include default spread (*DEF*), term spread (*TERM*), dividend yield (*DIV*) and the three month t-bill yield (*YLD*). The three Fama-French factors are the excess market return ($R_{mt} - R_{ft}$), size factor (*SMB*) and book-to-market factor (*HML*). Price momentum (*WML*) is contrasted in the manner as Table 2.2.The intra-industry momentum is computed in the manner described in Table 2.12. $\bar{R}^2$ is the time-series average of the monthly adjusted R^2.* Denotes significance at the 5% level.

	α_0	β_1	β_2	β_3	β_4	γ_1	γ_2	γ_3	γ_4	$\bar{R}^2$
					UK					
BASIC	-0.015*	0.338	-0.066	-0.013	0.776*	0.016	-0.015	0.031	0.377*	0.39
CYCGD	-0.006	0.022	0.056	0.139	-0.019	0.010	0.037	0.039	0.409*	0.43
CYSER	0.003	-0.059	0.023	0.091	0.051	0.012	0.005	0.026	0.560*	0.72
GENIN	-0.005	0.222	-0.029	-0.064	0.108	0.005	0.011	0.029	0.392*	0.60
ITECH	0.000	-0.632	0.442	0.067	-0.892	0.014	0.029	-0.056	0.569*	0.30
NCYCG	0.003	0.056	0.016	0.022	-0.093	-0.002	-0.001	-0.056	0.349*	0.26
NCYSR	0.015	-1.603*	0.349	0.556	1.171	-0.030	-0.071	-0.171	1.112*	0.49
RESOR	0.010	0.483	-0.218	-0.650*	-1.275*	-0.019	-0.101	-0.078	0.579*	0.32
TOTLF	-0.011*	0.176	-0.083	-0.042	0.649*	-0.006	-0.005	0.025	0.693*	0.73
OTHERS	0.002	0.428	-0.209	-0.163	1.009*	-0.023	-0.010	-0.157	0.508*	0.28
					Germany					
BASIC	-0.006	0.085	0.084	0.139	0.004	-0.001	0.012	-0.026	0.290*	0.27
CYCGD	-0.009	-0.101	0.228	0.477*	0.406	0.008	-0.020	-0.004	0.317*	0.29
CYSER	-0.004	-0.045	0.093	0.098	1.143*	0.021	0.024	0.008	0.799*	0.56
GENIN	0.002	0.011	-0.005	0.072	0.124	-0.002	0.023	0.009	0.419*	0.48
ITECH	0.128*	0.033	-1.878*	-3.207*	-0.780	0.068	-0.017	0.001	0.228*	0.40
NCYCG	-0.003	0.185	-0.012	-0.111	-0.125	-0.003	0.006	-0.012	0.391*	0.41
NCYSR	0.030	0.035	-0.493	-1.041	3.006*	0.014	0.018	-0.066	0.834*	0.34
RESOR	0.024	-0.341	-0.167	-0.359	0.284	0.013	-0.034	0.009	0.098	0.10
TOTLF	-0.012	0.063	0.129	0.346	-0.073	-0.009	-0.032	-0.045	0.339*	0.33
OTHERS	0.007	1.462	-0.322	-0.029	1.110	-0.104	-0.025	-0.126	-0.653*	0.17
					France					
BASIC	-0.011*	-0.119	0.135	0.252	0.316	0.010	0.003	-0.028	0.424*	0.18
CYCGD	0.024	-0.147	-0.102	-0.184	-0.148	0.048	-0.017	0.031	0.329*	0.11
CYSER	0.012	-0.075	-0.090	0.138	0.128	-0.029	-0.037	0.036	0.461*	0.28
GENIN	0.000	0.077	0.003	0.040	0.157	0.011	0.000	0.008	0.444*	0.27
ITECH	0.038*	-0.826	0.180	-0.601	-0.948	0.049	0.011	-0.103*	0.198	0.16
NCYCG	0.029*	0.965*	-0.633*	-0.589*	-1.013*	-0.045	0.008	0.023	0.286*	0.32
NCYSR	0.010	0.994*	-0.501*	-0.305	-0.715	0.013	-0.069	0.015	0.177	0.10
RESOR	0.047*	0.978*	-0.907*	-0.369	-0.535	-0.002	-0.032	0.005	0.454*	0.18
TOTLF	0.022	0.033	-0.224*	-0.082	-0.541	0.019	0.018	-0.002	0.354*	0.27
OTHERS	-0.075*	0.134	0.880*	1.267*	1.552*	-0.021	-0.033	-0.064	0.370*	0.46

2.5 Conclusions

This chapter investigates whether the apparent profitability of momentum trading can be explained by business cycle variables and behavioural characteristics in three major European markets namely France, Germany and the UK. The results show evidence of price momentum in all three countries. However, possibly due to some limitations inherent in the model, the predictive regression framework of Chordia and Shivakumar (2002) based on business cycle variables cannot capture momentum profits in these markets. The conditional asset pricing model of Avramov and Chordia (2006), that allows factor loadings to vary with firm specific variables, overcomes some of the limitations of the predictive regression model of Chordia and Shivakumar (2002). Therefore, this chapter also applies the Avramov and Chordia (2006) model to the European markets investigated. In line with the findings of Avramov and Chordia (2006), the chapter finds that momentum profits in Europe are largely attributable to asset mispricing that systematically varies with global business conditions. This confirms that the idiosyncratic component of stock returns does not play any prominent role in explaining momentum profits in European markets, but business cycle variables may offer a better explanation.

Inspired by the recent developments in the behavioural finance literature, especially by the ongoing debate on the role of investors' behaviour on price momentum, the Avramov and Chordia (2006) model is extended to incorporate behavioural variables. The results display a mixed role for behavioural variables across the countries, illustrating that investors' behaviour are less likely to be correlated to business cycle and unlikely to explain momentum profits. Moreover, the inclusion of behavioural variables does not affect the notion that momentum patterns are risk-based. This confirms that the findings of Avramov and Chordia (2006) hold for the major European financial markets and their model is robust to the inclusion of behavioural variables. Thus, the profitability of momentum strategies in Europe could be explained by risk factors, which are undetected 未被注意的 thus far and are largely attributable to the business cycle.

3. Limits to Arbitrage, Overconfidence and Momentum Trading

3.1 Introduction

Momentum trading strategies that take advantage of persistence in stock price movements short stocks that have recently performed poorly (out-of-favour stocks) to buy stocks that have recently performed well (favoured stocks). These strategies have attracted considerable attention from both practitioners and academics alike. In the UK, about 23 per cent of institutional traders are characterised as momentum traders (Keim, 2004). The importance of this trading strategy for practitioners is also evident from the introduction of momentum indexes to measure the intermediate-term momentum effects[15]. In the academic literature, profits from momentum trading strategies represent one of the main challenges faced by modern neo-classical based finance theory. Success of this strategy suggests that excess returns can be earned by observing prior changes in stock prices and thus rejects the prediction of the efficient market hypothesis. Momentum in stock returns has been observed internationally (see, for instance, Jegadeesh and Titman, 1993; Griffin et al., 2003) and attempts have been made to explain its causes. However, issues, such as what causes continuation in stock returns and whether momentum profits are genuine and exploitable or are only reflecting some kind of market imperfection/friction, have remained unresolved. This study addresses these issues.

Fama and French (1996) concede that their three-factor model fails to explain continuation in returns. Similarly, after controlling separately for systematic risk, size, price, book-to-market ratio, and the Fama-French three factors, Liu et al. (1999) confirm that significant momentum profits exist in the UK. Thus, the observed momentum in stock prices is not due to risk differences or firm specific factors. Alternative explanations of momentum in stock returns include market under-reaction to firm specific information (Jegadeesh and Titman, 1993; Chan et al., 1996); gradual diffusion of information (Hong and Stein, 1999; Hong et al., 2000); investors' behaviour (Barberis et al., 1998; Daniel et al., 1998); cross-sectional dispersion in unconditional and conditional expected returns (Conrad and Kaul, 1998; Chordia and Shivakumar, 2002);

[15] See, www.momentumindex.com.

market frictions such as trading costs, price impact and liquidity (Korajczyk and Sadka, 2004; Lesmond et al., 2004). Similarly, Hong et al. (2000) show that momentum profits are driven almost entirely by short-side portfolios and Ali and Trombley (2006) report that momentum profits are positively related to short-sale constraints.

Meanwhile, an alternative model that based on overconfidence and self attribution has been introduced by Daniel, Hirshleifer and Subrahmanyam (DHS, 1998) who suggest that over-reaction/overvaluation is the source of momentum profits. DHS suggest investors are overconfident about their private information, and therefore overweight their private information and under-react to public signals. When public information confirms investors' private information their confidence increases, investors continue to overreact to their priors because of biased self-attribution. The over-reaction in prices will eventually be corrected in the long run as investors observe future news and realise their error. As a result, increased overconfidence generates momentum in the short run and reversals in the long run. Along this line, Zhang (2006) use proxy of information uncertainty variables such as firm size, firm age, analyst forecast dispersion, leverage, return volatility, and cash flow volatility, shows that greater information uncertainty leads to relatively lower future stock returns following bad news and relatively higher future returns following good news, indicating that uncertainty prevents timely information incorporation into stock prices. The difference between the behaviour arguments such as DHS overconfidence model and Zhang (2006) information uncertainty arguments is that, the behaviour arguments focus on how investors with different biases react to information, while information uncertainty arguments focus on how information flow due to uncertainty, and therefore do not specify what kind of biases.

Miller (1977) theorised that stocks that are subject to both short-sale constraints and high dispersion in opinion are overvalued and generate low subsequent returns. This view rests on the argument that due to short-sale constraints, pessimistic traders cannot enter into the market and, hence, only optimistic investors continue to trade (buy) driving prices up, leading to overvaluation. Such overvaluation is maintained until the divergence in opinion is narrowed, at which point more investors realise that the stock is overvalued and start off-loading their holdings. If this prediction holds, stocks that were initially overvalued should earn low (negative) subsequent returns. Thus, Miller's views on the effects of short-sale constraints (a case of limits to arbitrage) and the divergence in opinion on the value of stocks can be extended to examine the possible reason(s) and exploitability of momentum profits[16]. Along this line, Ali and Trombley (2006) link an index of short-selling constraints to momentum profits, and this index includes both institutional ownership (the variable used here to measure short-sale constraints) as well as share turnover (the variable used here to measure differences of opinion). Chen, Hong, and Stein (2002) suggest that changes in breadth of ownership (which proxies for short sale constraints but is also correlated with differences of opinion in their model) are strongly related to momentum profits.

However, there is a fundamental problem of Miller's overvaluation hypothesis that the second condition – divergence in opinion – must be high in order to drive prices up. The problem lies in the fact that under any circumstance of disagreement, all stocks would only be bought by optimistic investors, so the number of pessimistic investors could only be observed from the short side. But if short selling is prohibited, the number of pessimistic investors is unobservable. As a result, the number of investors between optimistic and pessimistic is unknown. To illustrate the problem, if there are ten investors in the market, disagreement among investors is at the highest level if five are optimistic and five are pessimistic. Miller's hypothesis is correct only when the number of pessimistic investors is higher than the number of optimistic investors, since then it will fulfil the second condition that high disagreement leads to high overvaluation. On the other hand, if there are more optimistic investors than pessimistic investors, then a lower disagreement would means that more optimistic investors will buy and push prices upward. In spite of its plausibility, no prior study has explicitly examined the implications of both conditions of Miller's theory (limits to arbitrage and divergence in opinion) on momentum returns. This study fills this gap.

[16] Although some recent studies (for instance, Diether et al., 2002; Chen et. al., 2002) attempt to examine the overpricing hypothesis they do not consider the consequences of interaction between short-sale constraints and divergence in opinion simultaneously.

The distinction between Miller's Hypothesis and the DHS model is that, there are pessimistic investors in Miller's hypothesis, but these investors are constrained from shorting the stocks, whereas the DHS model suggests that representative investors who are overconfident drive the momentum effect. The ultimate question that lies between these two theories is to what extent do pessimistic investors contribute to overvaluation? The primary contribution of this study is to test whether the evidence is consistent with DHS model in addition to Miller's Hypothesis.

More specifically, this chapter aims to address three main questions that are still unresolved: (i) what are the sources of momentum profits? (ii) to what extent are momentum profits linked to overconfidence, limits to arbitrage and divergence in opinion? and (iii) are the apparent momentum profits exploitable?

Given the nature of equity ownership distribution, trading strategies adopted by major investors, opportunities available to professional investors to engage in short-selling and the availability of measures of variations in investors' opinion, the UK stock market is an excellent platform to test for the above issues on momentum in the context of Miller's proposition. Unlike many other developed markets, the UK financial institutions (active traders) hold a large proportion of equity traded on the London Stock Exchange (LSE). Recent statistics (The Office for National Statistics, 2006) suggest that at the end of December 2006, domestic institutions were holding 41.1 per cent (£762.8 billion) of equity traded on the LSE, only 12.8 per cent (£238.5 billion) were owned by individual shareholders and the rest were owned by foreign investors. Among the domestic institutions, insurance companies and pension funds are the major players in the market. Given that only one in four UK institutional investors are momentum traders[17] and short-selling is a professional activity used by institutional investors[18], opportunities to short-sell (arbitrage opportunities) should have implications on stock returns. D'Avolio (2002) shows that institutional investors are the main providers of stock loan supply. Therefore, using the details of institutional ownership this chapter can test for the

[17] Keim (2004) categorises 23 per cent of institutional investors as momentum traders.
[18] See Financial Services Authority (2006) for further details.

implications of arbitrage opportunities on momentum profits. Similarly, proxy measures of divergence in opinion (for example, analysts' forecasts) are also available for the UK. All of these offer an excellent opportunity to examine the implications of limits to arbitrage and divergence in opinion on momentum profits on the LSE.

This chapter arrives at several conclusions. First, using alternative proxies of limits to arbitrage this chapter find that momentum profits are driven almost entirely by loser stocks that are costly or impossible to short. The absence of their exploitability could explain the persistence in price momentum. Second, the limits in short-selling loser stocks defeat the idea of constructing a self-financing (hedge) portfolio to profit from momentum trading. High costs and/or the impossibility of short-selling out-of-favour stocks prohibit arbitrageurs from taking an appropriate position to exploit the profit opportunities and correct overpricing. Third, momentum profits originate from initial overvaluation brought about by excessively optimistic investors in the presence of limits to arbitrage (short-sale constraints), whereas, divergence in opinions do not play any role. The findings suggest that Miller's overvaluation hypothesis fails to explain the momentum profits. On the other hand, empirical evidence has been provided to support the DHS model that momentum profits are caused by overconfidence and self attribution bias. Finally, the known risk factors fail to explain the momentum profits. Therefore, momentum profits are caused by limits to arbitrage and overconfidence, hence, they are not easily exploitable.

The remainder of the chapter is organised as follows. Section 3.2 discusses limits to arbitrage and divergence in opinion and develops testable hypotheses. Section 3.3 describes the data and methodology. Section 3.4 empirically examines the relation between momentum profits and short-sale constraints and overvaluation. Section 3.5 provides tests of the DHS overconfidence model. Section 3.6 presents the cross-sectional regressions. Section 7 examines the relation between short sales constraints and the value premium. Section 3.8 concludes the chapter.

3.2 Theories and hypotheses development

3.2.1 Miller's overvaluation hypothesis

Miller (1977) shows that when there is a high level of uncertainty among investors about the value of a security, short-sale constraints could prevent pessimistic investors' opinion being incorporated into stock prices. In this scenario, optimistic investors can buy or continue to hold the stocks driving the prices up. However, due to short-sale constraints, pessimistic investors face limits on the sale side trade resulting in supply constraints and failure to bring the prices down. On balance, this leads to overpricing. Therefore, Miller's hypothesis requires two conditions to be satisfied: (a) short-sale constraints and; (b) divergence in investors' opinion. In a system where short-selling is permitted (both by regulations and transaction costs) pessimists can sell additional shares to optimists. This improves the supply causing the stock price to fall. However, Jarrow (1980) argues that the price of an individual stock can increase or decrease when short sales are allowed. For a strategy of buying favourable stocks with the proceeds from the short-sale of out-of-favour stocks to be profitable, the long position must outperform the short-position after accounting for transactions costs and the risks associated with short-selling. In reality, the costs and the risks of short-selling a stock could be prohibitive and, hence, we cannot be sure whether prices of stocks will change to reflect the balance of opinion. Moreover, Diamond and Verrecchia (1987) suggest that, under rational market conditions, other investors will identify the existence of short-sale constraints and will alter their own beliefs in a way to prevent the existence of overvaluation on average. Since the theoretical arguments on short-sale constraints and the overvaluation or undervaluation of stocks are inconclusive, the overpricing hypothesis is an empirical issue.

Miller's view is important to stock market anomalies that consist of short-side portfolios like value vs. growth, contrarian, and momentum trading strategies. If both growth stocks (in value vs. growth strategy) and loser stocks (in momentum trading) are impeded by short-sale constraints, the stocks will be overpriced resulting in lower subsequent returns. These low returns may be sufficient to produce the existence of an 'illusory premium'.

3.2.2 Limits to arbitrage and overvaluation

Direct costs of short-selling (a measure of arbitrage opportunities) are difficult to measure; therefore, studies use proxy measures. The costs of short-selling reflected in the stock loan market can be considered as a measure of constraints in selling short. Several studies (see, for example, D'Avolio, 2002; Mitchell et al., 2002) have analysed the market for borrowing stocks, however, their sample periods are rather short. On the other hand, Jones and Lamont (2002) analysed the NYSE 'loan crowd' rebate rate[19] as the proxy for the cost of short-selling with a longer sample period. Their findings suggest that stocks that are expensive to short or that enter the lending market with high valuations tend to have low subsequent returns.

Some studies (see, for example, Figlewski, 1981; Dechow et al., 2001) measure the demand for short-sales with short-interest. However, this measure also suffers from some limitations. Short-interest represents the net short positions outstanding in the stock as of the settlement date, stocks that are difficult and expensive to short will have low short-interest. Stocks that are impossible to short have an infinite shorting cost; however, the level of short-interest is zero. To illustrate, Lamont and Thaler (2003) examine a sample of technology carve-outs that appeared to be overpriced. They show that the apparent overpricing and the implied cost of shorting fall over time, while the level of short-interest rises. As such, short-interest can be negatively correlated with the demand for shorting, overpricing, and the cost of shorting. These limitations weaken the reliability of empirical findings based on short-interest.

Another proxy measure of short-sale constraints is lack of institutional ownership. D'Avolio (2002) shows that stocks with low institutional ownership are likely to be 'special' and expensive to borrow. This view rests on the principle of demand and supply of stocks in the stock-loan market. Short-sellers must borrow the stocks and return them on demand. The cost of shorting is likely to be lower for stocks with substantial institutional ownership, since it is easier to find alternative lenders of such stocks. Nagel (2005) employs institutional ownership as a proxy for short-sale constraints, and finds

[19] The rebate is the interest earned on the proceeds from the sale of borrowed shares.

that the book-to-market effect, in particular the underperformance of growth stocks, is primarily concentrated in stocks that are difficult to short. He suggests that the overpricing hypothesis is behind the book-to-market anomaly. Similarly, Phalippou (2007) confirms that the value premium is created by a few overvalued stocks that are difficult to sell short, and suggests that limited arbitrage, rather than risk, plays a major role in the existence of the value premium. Ali and Trombley (2006) report that momentum profits are higher from stocks that experience high short-sale constraints and the results are mainly driven by loser stocks. Although they suggest that momentum returns are positively related to the cost of short-selling, they do not test the hypothesis that divergence in opinion drives the price/profit of stocks that are difficult to short. Therefore, this chapter hypothesises that 'there is a positive association between momentum profits and short-sale constraints'.

3.2.3 Interaction between short-sale constraints and dispersion in opinion

Another factor that Miller (1977) attributes to overvaluation is high divergence in opinion. Scherbina (2001) used dispersion in analysts' earnings forecasts (I/B/E/S) as a proxy for divergence in opinion and shows that the highest dispersion in opinion portfolio earns a lower average return than the lowest dispersion in opinion portfolio. Chen et al. (2002) used breadth of ownership as a proxy for divergence in opinion and found that when few mutual fund managers have long positions in a given stock (low breadth of ownership), prices are high relative to fundamentals and that when the breadth decreases, subsequent returns decline. Danielsen and Sorescu (2001) contend that exchange-traded options mitigate short-sale constraints and examined the effects of option listings on the prices of underlying securities. They considered four measures of dispersion in investors' belief[20]. Their results generally support the conjecture that stock options mitigate the short-sale constraints that would otherwise lead to overvaluation. Diether et al. (2002) show that stocks with higher dispersion in analysts' earnings forecasts earn significantly lower future returns than otherwise similar stocks. Such results suggest that disagreement in

[20] The four proxies of dispersion in investors' opinion they used are: (a) the standard deviation of weekly (five-day) raw returns from day t-250 to date t-6; (b) the standard deviation of the error terms of the market model estimated from day t-100 to date t-6 relative to the event date; (c) the *ex ante* mean daily trading volume and; (d) the dispersion of analysts' forecast.

investors' opinion is priced at a discount as we would expect under Miller's hypothesis. Previous studies on the overpricing hypothesis do not consider the interaction of short-sale constraints and differences in opinion simultaneously – i.e. they do not examine the central theme of Miller's hypothesis. This chapter tests for the implications of such an interaction on momentum returns. This section hypothesises that 'momentum profits are high when both short-sale constraints and divergence in investors' opinion are high'.

3.2.4 Overconfidence and momentum profit

Stocks with good past performance tend to attract investors' attention. Behavioural models predict that traders are either slow to react or over-react to good news. The optimistic investors, usually less sophisticated[21], tend to rely on their own private information/beliefs in determining the firm's future cash flows. As noted by Daniel et al. (1998), when public information confirms investors' private information their confidence increases. Disconfirming public news draws less attention and the investor's confidence in their private signals remains unchanged. It is also consistent with a particular type of representativeness bias, the law of small numbers in which people expect even a small sample to reflect the properties of the entire population[22]. In this case, if investors perceive some good news about a firm, they will continue to believe that the stock will do well in the future. This belief will escalate his/her confidence level, create the self attribution bias and lead to excessive optimism about the firm. In addition, short-sale constraints prevent a timely incorporation of bad news into prices. In other words, the negative opinion of pessimistic investors is not incorporated in market price. This suggests a testable proposition that 'there is a positive association between momentum profits and short-sale constraints and high momentum profits are associated with more good public news'.

Tests of the above propositions are important as they shed light on how the mispricing

[21] Indeed, Barber and Odean (2007) show that small investors are more likely to trade in stocks that have had recent extreme performance, possibly due to attention effects.

[22] To illustrate, suppose that an investor sees many periods of good earnings, the law of small numbers leads her to believe that earnings growth has gone up, and thus earnings will continue to remain high in the future.

arises that eventually generates the predictability of stock returns, and indeed, the momentum profits. This chapter examines whether Millers overpricing hypothesis based on limits to arbitrage and the DHS model based on overconfidence can explain the underperformance of loser stocks and the momentum anomaly.

3.3 Data and methods

3.3.1 Data

For the reasons stated earlier, the LSE is an excellent platform for testing the implications of limits to arbitrage and divergence in investors' opinion on momentum profits. On the LSE, the regulations on short-selling are fairly relaxed for institutional investors[23]. They also hold a large fraction of stocks traded on the LSE and are active in short-selling. Although direct observations on short-sale contracts are not available, as evident from the studies of D'Avolio (2002) and Nagel (2005), the distribution of institutional ownership (hereafter IO) offers an excellent proxy of the possibilities of stock loan supply[24]. Therefore, this chapter uses ownership distribution as a measure of constraints to sell short; stocks with lower institutional holdings experience higher short-sale constraints.

The data on ownership distribution comes from the PricewaterhouseCoopers Corporate Register published by Hemmington-Scott. For each company, this unique database records the name of each shareholder and his/her proportion (per cent) of share holdings (ordinary share capital). To improve the comparability of my results with US studies that use the CDA/Spectrum Institutional Holdings (13F) database, this chapter extract quarterly institutional holdings from the Hemmington-Scott databases[25]. This chapter then match (manually) the ownership database with Datastream[26]. First, for each company, institutions that are holding 3 per cent or more of its equity shares are identified. Then, the total institutional holding of the company is estimated by adding the holdings of all institutions identified in the first step. If no record of institutional holding is available, it

[23] See Financial Services Authorities (2006) for further details.

[24] For an excellent discussion on the relation between short-sale constraint and institutional ownership see Nagel (2005).

[25] For the definition of institutional investors, this chapter follows the CDA/Spectrum Institutional Holding database in order to provide comparable results.

[26] While merging these data bases this chapter uses Lexis-Nexis and FAME to identify company name changes.

is considered zero. The sample excludes financial companies. The final sample consists of 86,151 observations for 2,556 unique firms from January 1993 to December 2002. This choice of sample period has been guided by the availability of ownership data at the time of data collection[27].

3.3.2 Residual institutional ownership (RIO)

Earlier evidence (see, for example, Nagel, 2005) shows a high degree of association between firm size and institutional ownership (INST). Therefore, as in Nagel (2005), this section measures short-sale constraints by residual institutional ownership adjusted for firm size[28]. Given that the degree of institutional ownership is a proportion ranging from 0 to 1, the residuals will not be normally distributed. Therefore, before controlling for the firm size a logit transformation is applied on INST (equation (3.1)).

$$(3.1) \qquad \text{Logit}(\text{INST})_{i,t} = \log\left(\frac{\text{INST}_{i,t}}{1-\text{INST}_{i,t}}\right)$$

If INST is below 0.0001 or above 0.9999 it is replaced with 0.0001 and 0.9999 respectively. In equation (3.1) i,t represents firm i at time t (quarter). To control for any size effect, this section estimate equation (3.2):

$$(3.2) \qquad \text{Logit}(\text{INST})_{i,t} = \alpha + \beta \ln S_{i,t} + \varepsilon_t$$

Where, $S_{i,t}$ is the market capitalisation of firm i at time t. This cross-sectional equation is estimated for the period between January 1993 and December 2002. The residual (ε_t) of equation (3.2) is the residual institutional ownership (RIO). This allows us to measure the variation in institutional ownership, holding the firm size fixed.

3.3.3 Momentum trading strategies

For the computation of momentum profits, this chapter follow the most common used 6 x

[27] Appendix 4 reports the summary statistics on firm characteristics used in this chapter.
[28] The method used in this sub-section is based on Nagel (2005).

6 momentum strategy[29], for instance, for each month t, all stocks are allocated into three (or five) portfolios (P=1 to 3) based on their six-month formation-period (t-7 to t-2) returns. Portfolio P1 (i.e. P=1) is an equally weighted portfolio of stocks in the worst-performing 30 per cent stocks, portfolio P2 (i.e. P=2) contains the middle 40 per cent stocks, and portfolio P3 (i.e. P=3) comprises the best-performing 30 per cent stocks. The position is held for the following six-month period (t_0 to t+5). This chapter employs a one month gap between the formation and the holding period to avoid the momentum effect with short-term price reversals and the bid-ask bounce effects established by previous studies (see, for example, Jegadeesh, 1990; Jegadeesh and Titman, 1995). Throughout this chapter, unless otherwise stated, equally weighted portfolio returns have been used.

3.3.4 Divergence in investors' opinion (Disp)and trading volume (VO)

This section measures the divergence in investors' opinion by the dispersion in analysts' earnings per share (EPS) forecasts[30]. The dispersion in analysts' EPS forecasts is defined as the standard deviation of EPS forecasts scaled by the stock price per share at the beginning of forecast's fiscal year. Both the standard deviation of EPS forecasts and corresponding share prices are obtained from the I/B/E/S Summary History file. To allow for the calculation of standard deviation, only the stocks followed by at least two analysts are included in the sample. Data on trading volume are obtained from Datastream. Trading volume is measured as the ratio of the number of shares traded to the number of shares outstanding.

3.3.5 Analyst recommendations (Rec)

Analyst recommendations rate stocks as 'strong buy,' 'buy,' 'hold,' 'sell,' and 'strong sell.' Analysts also use other labels such as 'market underperform' and 'market outperform,' or 'underweight' and 'overweight,' to convey their opinions, but I/B/E/S standardizes the recommendations, and converts them to numerical scores where '1' is strong buy, '2' is buy, and so on. This section then group the sample into three parts: 1)

[29] This chapter also reports the 3x3, 6x6, 9x9 and 12x12 momentum strategies in Appendix 5, momentum profits from the 6x6 strategy is indeed the highest.

[30] Diether et al. (2002), among others, use analysts' EPS forecasts as a measure of divergence in opinion.

Buy portfolio which contains both 'strong buy' and 'buy' recommendation, 2) Hold portfolio which contains recommendation of holding the stock, 3) Sell which contains both 'strong sell' and 'sell' recommendation.

3.3.6 Analyst forecast revisions (FRev)

Analyst forecast revisions for the current month are split into 'up revision', 'no change' and 'down revision'. This chapter standardizes the forecast revision, and converts them to numerical scores where '1' is 'up revision', '0' is 'no change', and '-1' is 'down revision'. Forecast revisions are unadjusted for stock splits using the adjustment factors because of the split-adjustment bias detailed in Diether, Malloy, and Scherbina (2002) provided by I/B/E/S.

3.4 Momentum profits, short-sale constraints and overvaluation

3.4.1 Short-sale constraints and gross returns from momentum trading

To examine the hypothesis that 'there is a positive association between momentum profits and short-sale constraints', this section sort all stocks into quintiles at the end of each month t based on their returns during the six month formation period (t-7 to t-2). This section then group the stocks of each price momentum category into five portfolios (equal stocks) on the previous quarter's RIO obtained from equation (3.2)[31]. Portfolios are formed at different points during the year. Such overlapping portfolios increase the power of tests (see Jegadeesh and Titman, 1993). To avoid the momentum effect with very short-term price reversals and the bid-ask bounce effects, this section allows for a one month gap between the formation period and the holding period. The portfolios are held for the subsequent six months (t_0 to t+5). Newey-West (1987) standard errors (adjusted for serial dependence caused by the use of overlapping lagged data) are used.

The results in Table 3.1 (panel A) support the predictions that momentum profits are most pronounced in loser stocks with high short-sale constraints. The average difference

[31] In a further test, this chapter replaces residual institutional ownership with institutional ownership (i.e. without adjusting for size). The results are qualitatively similar.

between the monthly returns of winner (P5) and loser (P1) portfolios in the lowest RIO quintile is 1.81 per cent (*T*-statistic = 4.98). In contrast, the differences between returns of P5 and P1 in RIO4 and RIO5 portfolios are statistically insignificant. The results (panel A) also show that almost all of the contribution to momentum profits comes from loser stocks. Besides, momentum returns (P5-P1) decrease monotonically with the increase in RIO quintiles suggesting that momentum of loser stocks can be exploited by selling the stocks short. This confirms the importance of opportunities to short-sell in exploiting momentum profit. Figure 3.1 depicts the momentum profits against the RIO quintiles and confirms that momentum profits from the lowest two quintiles are caused by the tendency of loser stocks to lag behind. This evidence supports the hypothesis that 'there is a positive association between momentum profits and short-sale constraints'.

Table 3.1 Raw Returns by Price Momentum and Short-sale Constraints

Average monthly raw returns (per cent) of portfolios composed on price momentum and three measures of short-sale constraints are reported. At the end of each month *t*, all stocks are allocated into five price portfolios (P1, P2,..., P5) based on their returns during the six month formation-period (*t*-7 to *t*-2). Stocks in each price portfolios are grouped into five further portfolios for each measure of short-sale constraints. The measures of short-sale constraints are: (a) previous quarter's residual institutional ownership (RIO), Panel A; firm size (S), Panel B; and the presence of exchange-traded options and/or futures, Panel C. RIO is the residual of equation (3.2). Firm size (S) is measured by market capitalisation. All portfolios are equally weighted. The position is held for six-months (*t* to *t*+5). *T*-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) per cent level. The sample period is January 1993 to December 2002.

Panel A: Residual Institutional Ownership (RIO)

	RIO1 (Low)	RIO2	RIO3	RIO4	RIO5 (High)	RIO1–RIO5
P1 (Loser)	-1.81	-1.64	-1.27	-1.45	-1.16	-0.65 (-1.80**)
P2	-0.99	-0.98	-0.91	-1.17	-0.96	-0.02 (-0.07)
P3	-0.87	-1.20	-0.71	-1.29	-0.93	0.07 (0.20)
P4	-0.58	-0.60	-0.65	-0.85	-0.72	0.14 (0.41)
P5(Winner)	0.00	-0.38	-0.45	-0.70	-0.64	0.64 (1.53)
P5 – P1	1.81 (4.98*)	1.26 (3.24*)	0.83 (2.01*)	0.76 (1.85**)	0.52 (1.23)	1.30 (3.79*)

Panel B: Size (S)

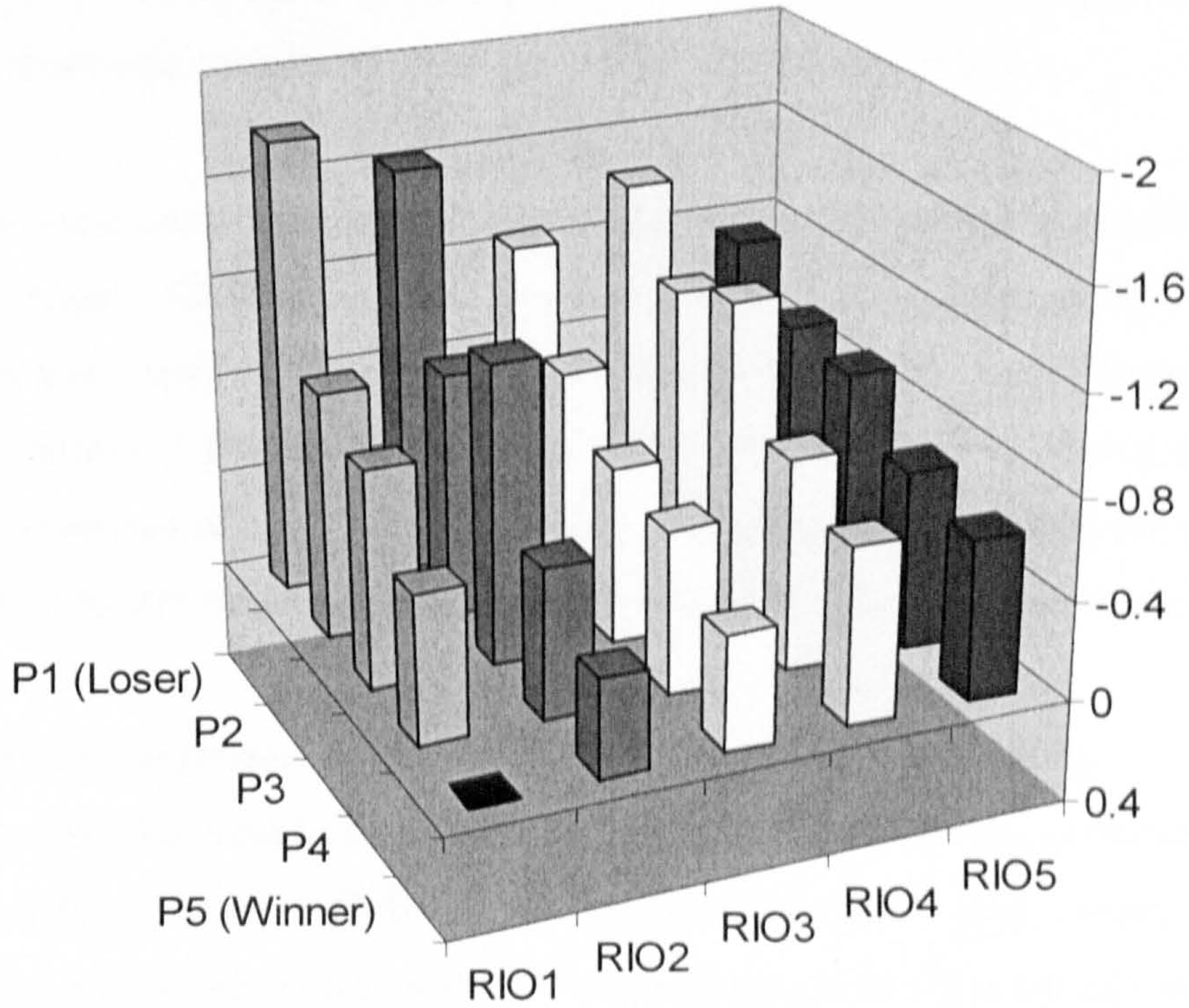
	S1 (Low)	S2	S3	S4	S5 (High)	S1 – S5
P1 (Loser)	-2.53	-2.24	-1.92	-1.79	-1.33	-1.20 (-2.40*)
P2	-0.73	-1.24	-1.82	-1.44	-0.91	0.18 (0.51)
P3	-0.52	-0.75	-1.00	-0.89	-0.60	0.08 (0.28)
P4	-0.15	-0.31	-0.39	-0.40	-0.23	0.08 (0.29)
P5(Winner)	-0.16	-0.23	-0.27	-0.43	-0.07	-0.09 (-0.24)
P5 – P1	2.37 (5.13*)	2.01 (5.27*)	1.64 (3.79*)	1.37 (2.94*)	1.26 (3.00*)	1.11 (2.88*)

Panel C: Individual options and futures

	Without options and futures = 1	With options and/or futures = 0	1 - 0
P1 (Loser)	-2.14	-0.47	-0.35 (-1.09)
P2	-0.78	0.13	-0.91 (-3.25*)
P3(Winner)	-0.17	0.18	-2.01 (-3.61*)
P3 – P1	1.97 (4.86*)	0.65 (1.63)	

Figure 3.1 Residual Institutional Ownership and Momentum Profits

The graph corresponds to the result of Table 3.1 (Panel A). At the end of each month *t*, all stocks are allocated into quintile based on their six-month formation-period from *t*-7 to *t*-2 and by proxies of short sales constraints: the end of the previous quarter residual institutional ownership (RIO). Quintile portfolios are formed monthly by weighting equally all firms in that quintile ranking. The position is held for the following six-month period (*t* to *t*+5). This figure reports the strategy's mean raw returns during the holding period.



This chapter examines the robustness of the above findings using alternative measures of short-sale constraints. Some earlier studies (for example, Chen et al. (2002) and Diether et al. (2002)) suggest that firm size can be a proxy measure of stocks available for short-selling. Therefore, to examine whether momentum profit is firm size dependent this section groups the sample stocks on their market capitalisation and estimate momentum profits. The results show that momentum profit is inversely related to firm size and most of the profits come from loser stocks (Table 3.1, panel B). This reconfirms that loser stocks that have short-sale constraints make a substantive contribution to momentum profits. Next, it is also possible that the presence of exchange-traded options and/or futures can serve as a route to short-sales, and therefore, reduce the consequences of constraints in short-selling. Only 108 sample firms have individual traded options and/or futures. To maintain a reasonable number of stocks in each portfolio this section sorts them into three groups (as opposed to quintiles). P1 includes the worst performing 30 per cent stocks, P2 includes the middle 40 per cent stocks, and P3 includes the best performing 30 per cent stocks. The results in Table 3.1 (panel C) show that stocks that have individual options and futures experience significantly lower momentum profits than other stocks. These results reconfirm earlier findings that stocks, especially the loser stocks, with short-sale constraints generate higher momentum profits.

Overall, short-sale constraints play a significant role in generating momentum profits. Considering Nagel's (2005) view that size can proxy for many other things, rather than just the short-sale constraints, and only limited observations are available on individual options and futures I believe that the RIO can serve as the best proxy (among the available alternatives) of short-sale constraints. Moreover, RIO accounts for size effects. Therefore, this chapter measures short-sale constraints by RIO in further analysis.

3.4.2 Short-sale constraints and excess returns from momentum trading

It is possible that the observed momentum profit discussed in the previous section is simply a manifestation of differences in risk premium rather than excess returns. To account for this possibility, this section estimates excess returns that are adjusted for three benchmark returns, viz. (a) market-adjusted, (b) Fama-French three-factor adjusted, and (c) industry adjusted. The market-adjusted return (raw return less the market return) of each stock is estimated for the end of each month t. Portfolios are formed on such market adjusted returns. Although the excess returns (Table 3.2, panel A) are smaller than gross returns, the overall findings support the earlier findings that the momentum profits come from loser stocks that face higher short-sale constraints. This evidence suggests that risk differences cannot explain momentum profits.

Contemporary finance literature advocates the superiority of the Fama-French three factor model against other single factor models (see, for instance, Davies et al., 1999). Therefore this section estimates the returns that are adjusted for three risk factors as in equation (3.3):

(3.3) $R_{P,t} = \alpha + \beta_{Mkt}(R_{Mkt} - R_F)_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \varepsilon_t$

Where, $R_{P,t}$ is raw return from portfolio p (for p = 1 to 25, as in Table 3.1), R_{Mkt} is market return measured by the FTSE All share index, R_F is the risk-free rate measured by the return on three-month Treasury bills, SMB and HML are small minus big, and high minus low as defined in Fama and French (1996)[32]. A significant α (alpha) in equation (3.3) represents excess return that is not explained by the three risk factors. Table 3.2 (panel B) documents the excess returns (alpha of equation 3.3) for each of the 25 portfolios. The estimates confirm that the adjustment for risk using the three-factor model does not alter the earlier conclusion that momentum profits originate largely from loser stocks with high short-sale constraints (i.e. low RIO). In fact, the three risk factors adjusted returns are slightly higher than the raw returns. In summary, this suggests that the Fama-French three factor model cannot explain momentum profits.

Finally, some earlier studies show that stock returns could be industry specific reflecting business cycle conditions. To allow for this possibility, this chapter estimates the industry adjusted excess return of each stock (stock return *minus* return on industry portfolio)[33]. This method implies that stocks are as risky as their industry peers. The results in Table 3.2 (panel C) show that part of the industry adjusted momentum profits comes from winner stocks but a substantial part of momentum profits comes from loser stocks. More importantly, momentum profits are concentrated mainly in high short-sale constraint (low RIO) stocks. Therefore, the results reported in earlier paragraphs are not driven by industry effects. Overall, the results that loser stocks characterised by short-sale constraints contribute most in momentum profits continue to hold even after controlling for known risk and industry factors.

[32] I thank Stefan Nagel for providing the factor returns data. Since his data is only available until 2001, I follow his methodology to construct the factors for the year of 2002. His methodology is important as the construction of the factors captures the unique characteristics of UK data (see also Dimson et al. 2003 for details).
[33] The industry classifications are obtained from Datastream (INDC3).

Table 3.2 Excess Returns by Price Momentum and Short-sale Constraint

Average monthly excess returns (per cent) of portfolios composed on price momentum and short-sale constraint are reported. Short-sale constraint is measured by the RIO, the residual of equation (3.2). At the end of each month *t*, all stocks are allocated into five price portfolios (P1, P2,..., P5) based on their returns during the six month formation-period (*t*-7 to *t*-2). Stocks in each price portfolios are grouped into five further portfolios on each bench-mark adjusted returns. Bench-marks adjusted excess returns are estimated as: *first*, individual stock returns are adjusted for the market (FTSE All share index) returns, Panel A; *second*, individual stock returns are adjusted for Fama-French three factors, Panel B; and *third*, individual stock returns are adjusted for industry returns, Panel C. Industry portfolios are formed using the Datastream's industry-classification (data type: INDC3). All portfolios are equally weighted. The position is held for six-months (*t* to *t*+5). *T*-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) per cent level. The sample period is January 1993 to December 2002.

	Residual Institutional Ownership					
Momentum	**RIO1 (Low)**	**RIO2**	**RIO3**	**RIO4**	**RIO5 (High)**	**RIO1 – RIO5**
	Panel A: Market Adjusted Returns					
P1 (Loser)	-2.18	-1.92	-1.68	-1.43	-1.23	-0.96 (-2.35*)
P2	-1.24	-1.01	-0.98	-0.65	-0.59	-0.66 (-2.72*)
P3	-0.74	-1.01	-0.42	-0.36	-0.08	-0.66 (-3.12*)
P4	-0.40	-0.42	-0.27	-0.21	-0.07	-0.33 (-1.70**)
P5(Winner)	-0.09	-0.13	-0.03	0.14	0.01	-0.10 (-0.37)
P5 – P1	2.09 (6.20*)	1.79 (5.77*)	1.65 (5.09*)	1.57 (4.17*)	1.24 (3.51*)	0.85 (2.17*)
	Panel B: Three-factor Adjusted Returns					
P1 (Loser)	-2.26	-2.26	-1.69	-1.93	-1.66	-0.60 (-1.81**)
P2	-1.40	-1.41	-1.32	-1.61	-1.44	0.04 (0.47)
P3	-1.28	-1.58	-1.11	-1.71	-1.32	0.04 (0.20)
P4	-1.01	-1.01	-1.02	-1.30	-1.14	0.13 (0.42)
P5(Winner)	-0.42	-0.66	-0.81	-1.08	-0.98	0.56 (1.55)
P5 – P1	1.84 (5.01*)	1.61 (3.82*)	0.88 (2.03*)	0.85 (1.86**)	0.68 (1.24)	1.16 (3.79*)
	Panel C: Industry Adjusted Returns					
P1 (Loser)	-1.39	-1.35	-1.18	-0.59	-0.31	-1.08 (-4.54*)
P2	-0.08	-0.22	-0.18	-0.38	-0.37	0.28 (2.10*)
P3	0.36	0.14	0.34	0.06	0.08	0.28 (2.04*)
P4	0.59	0.45	0.33	0.27	0.27	0.32 (3.17*)
P5(Winner)	0.59	0.38	0.28	0.21	0.10	0.48 (2.37*)
P5 – P1	1.98 (5.09*)	1.73 (6.47*)	1.45 (3.66*)	0.80 (1.92**)	0.41 (1.42)	1.57 (5.72*)

3.4.3 Divergence in opinion and excess returns from momentum trading

Miller (1977) suggests that stocks that are subject to both short-sale constraints and high divergence in investors' opinion are overpriced. To test this conjecture along with momentum profits, this section first sorts stocks in quintiles (for each *t* month) on the previous quarter's residual institutional ownership (RIO) – a proxy for short-sale constraints. Next, stocks in each RIO portfolios are sorted into three groups on dispersion in analysts' EPS forecasts during the three months prior to the first day of the portfolio formation period (Disp). RIO, a measure of short-sale constraints, is obtained from equation (3.2). Next, three equally weighted portfolios are formed on their prior price performance. Portfolio P1 consists of the 30 per cent worst-performing stocks, portfolio P2 contains the middle 40 per cent, and portfolio P3 includes the 30 per cent best-performing stocks. This three dimensional analysis allows us to test the hypothesis that momentum profits are high when both short-sale constraints and divergence in investors' opinion are high.

The estimates in Table 3.3 show that momentum profit is concentrated in low RIO stocks (high short-sale constraints), and is driven by loser stocks. Within each RIO portfolio, although momentum profit is most pronounced on the portfolio of stocks with high dispersion in analysts' EPS forecasts, there is no statistical difference between high dispersion and low dispersion portfolios (even among low RIO stocks).

This result is consistent with the earlier findings that short-sale constraints are important in determining the magnitude of momentum profits. However, returns across divergence in opinion portfolios are not statistically important. The findings show that the overpricing hypothesis of Miller (1977) fails to explain the sources of momentum profits.

As a robustness check, this chapter uses trading volume as an alternative proxy for the dispersion of investor beliefs. Table 3.4 reports the average monthly raw returns during the holding period (t to t+5). The result shows that momentum profits (P3-P1) are driven substantially by the loser stocks. In addition, momentum returns are concentrated on the lowest two RIO quintiles, and decrease monotonically across RIO quintiles. This result is consistent with the earlier findings that short sales constraints are important in determining the magnitude of momentum profits. However, returns are statically insignificant across VO portfolios. Using alternative measures of divergence in opinion, this section shows that the overpricing hypothesis of Miller (1977) fails to explain the sources of momentum profits.

Table 3.3 Momentum Returns by Short-sale Constraint and Divergence in Opinion (Dispersion in Analysts' EPS Forecasts)

Average monthly raw returns (per cent) of portfolios composed on short-sale constraint and divergence in opinion are reported. Short-sale constraint is measured by the RIO, the residual of equation (3.2). Divergence in opinion on each stock is measured by the standard deviation in EPS forecasts made in 3-months prior to the formation period scaled by the stock price per share at the beginning of the month of forecast. First, at the end of each month *t*, all stocks are allocated into three RIO portfolios. Second, stocks in each RIO portfolio are grouped into 3 further portfolios on divergence in opinion (Disp). All stocks belonging to each element of the (RIO x Disp) matrix are then grouped into three portfolios. The portfolios are P1 (the worst performing 30 per cent), P2 (the middle 40 per cent), and P3 (the best performing 30 per cent). The position is held for six-months (*t* to *t*+5). All portfolios are equally weighted. *T*-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) per cent level. The sample period is January 1993 to December 2002.

	Dispersion in Analysts' EPS Forecasts portfolios			
RIO Portfolios	Disp3 (High)	Disp2	Disp1 (Low)	Disp3 – Disp1
RIO1 (Low)	P3 = -0.20 P1 = -2.49 P3 – P1 = 2.28 (4.12*)	P3 = -0.32 P1 = -2.04 P3 – P1 = 1.72 (2.99*)	P3 = -0.15 P1 = -1.72 P3 – P1 = 1.57 (2.82*)	P3 – P1 = 0.59 (0.81)
RIO2	P3 = -0.08 P1 = -1.54 P3 – P1 = 1.45 (2.89*)	P3 = -0.48 P1 = -1.54 P3 – P1 = 1.06 (1.89**)	P3 = -0.67 P1 = -1.71 P3 – P1 = 1.04 (1.77**)	P3 – P1 =0.38 (0.56)
RIO3 (High)	P3 = -0.69 P1 = -1.00 P3 – P1 = 0.31 (0.43)	P3 = -0.22 P1 = -0.55 P3 – P1 = 0.34 (0.63)	P3 = -0.81 P1 = -0.87 P3 – P1 = 0.06 (0.10)	P3 – P1 =0.25 (0.34)
RIO1 – RIO3	P3 – P1 = 1.97 (2.66*)	P3 – P1 = 1.07 (1.45)	P3 – P1 = 1.50 (2.00*)	

Table 3.4 Mean monthly momentum profits by residual institutional ownership and trading volume

All stocks are first sorted each month t into quintile based on the end of previous quarter residual institutional ownership (RIO) and then 3-month period trading volume (VO) prior to the first day of the formation period (t-7 to t-2). RIO is obtained from a cross-sectional regression using eq. 3.2. Trading volume is measured as the ratio of the number of shares traded to the number of shares outstanding. Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30%, portfolio P2 contains the middle 40%, and portfolio P3 includes the best-performing 30%. This table reports the portfolio's mean raw returns during the holding period (t to t+5). t-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**)denotes significance at the 5(10)% level. The sample period is January 1993 to December 2002.

	VO3 (High)	VO2	VO1 (Low)	VO3 – VO1
RIO1 (Low)	P3 = 0.71 P1 = -2.06 P3 – P1 = 2.77 (5.32*)	P3 = 0.65 P1 = -1.78 P3 – P1 = 2.43 (5.19*)	P3 = 0.09 P1 = -1.91 P3 – P1 = 2.00 (4.11*)	P3 – P1 = 0.77 (1.28)
RIO2	P3 = 0.78 P1 = -1.81 P3 – P1 = 2.58 (4.92*)	P3 = 0.37 P1 = -1.75 P3 – P1 = 2.11 (3.74*)	P3 = -0.41 P1 = -2.03 P3 – P1 = 1.62 (3.08*)	P3 – P1 = 0.97 (1.60)
RIO3	P3 = -0.03 P1 = -1.24 P3 – P1 = 1.21 (2.55*)	P3 = -0.01 P1 = -0.82 P3 – P1 = 0.81 (1.36)	P3 = -0.28 P1 = -0.84 P3 – P1 = 0.57 (1.09)	P3 – P1 = 0.64 (1.09)
RIO4	P3 = 0.20 P1 = -0.37 P3 – P1 = 0.57 (1.07)	P3 = 0.23 P1 = -0.42 P3 – P1 = 0.65 (1.20)	P3 = -0.29 P1 = -0.77 P3 – P1 = 0.48 (0.94)	P3 – P1 = 0.09 (0.14)
RIO5 (High)	P3 = 0.01 P1 = -0.37 P3 – P1 = 0.38 (0.78)	P3 = -0.10 P1 = -0.66 P3 – P1 = 0.56 (1.23)	P3 = -0.30 P1 = -0.79 P3 – P1 = 0.49 (0.86)	P3 – P1 = -0.11 (-0.19)
RIO1 – RIO5	P3 – P1 = 2.40 (3.79*)	P3 – P1 = 1.87 (3.99*)	P3 – P1 = 1.51 (2.76*)	

In summary, the findings of this section have major implications for trading. First, momentum returns are more likely to be 'paper' returns as these profits primarily come from loser stocks that are very costly or impossible to short. Second, investors' inability to short-sale loser stocks defeats the original idea of generating momentum profits from a self-financing (hedge) portfolio. The persistence in momentum in stock prices is therefore caused by limits to arbitrage rather than investors' under-reaction to firm-specific information reported in some earlier studies. Some behavioural finance theorists argue that the persistence in momentum profits may be attributed to the disposition effect, implying that investors are reluctant to sell losers and eager to dispose of winners (see Shefrin and Statman, 1985). Ranguelova (2001) points out that the disposition effect operates entirely through the selling behaviour of individual investors. However, in this case, individual (unsophisticated) investors are not assumed to be subject to any irrational behaviour/bias in their selling decisions[34]. This chapter only assumes that short-sale constraints prohibit arbitrageurs from immediately correcting mispricing.

Institutional investors generally do not hold momentum (loser) stocks and less sophisticated individual investors are unlikely try to get involved in short-selling. These trading behaviours of investors help maintain persistence in momentum profits that come from loser stocks. The finding of Keim (2004) that only 23 per cent of institutional traders in the UK are characterised as momentum traders (50 per cent are index/diversified traders and 27 per cent are value/fundamental traders) suggests that momentum strategies are less popular among British institutional investors. Finally, the findings suggest that Miller's overpricing hypothesis cannot fully explain the momentum profits.

3.5 A test of DHS's overconfidence model and momentum profit

Discussions in the previous section confirm that momentum profit originates mainly from the underperformance of loser stocks, and the continued underperformance is concentrated in stocks with high short-sale constraints but not with high divergence in investors' beliefs. This section tests an alternative overvaluation theory developed by Daniel, Hirshleifer and Subrahmanyam (DHS, 1998) suggesting that overconfidence and self attribution are the sources of momentum profits. DHS suggest investors are overconfident about their private information, and therefore overweight their private information and under-react to public signals. When public information confirms investors' private information their confidence increases, investors continue to over-react to their priors because of biased self-attribution. This optimism, generally excessive,

[34] The problem of using the disposition effect to explain the persistence of momentum profits is that it requires investors to consistently reject selling their stock. While it may be true that individual investors are sometimes reluctant to sell assets that are trading at a loss, it is hard to believe that they always do so.

together with short-sale constraints leads to overvaluation resulting in subsequent low returns.

To test this proposition, this section uses short-sale constraints to capture optimistic investors, since pessimistic traders cannot enter into the market and, hence, only optimistic investors remain in the market. This section employs analyst recommendations and analyst forecast revisions to capture *good* public information in which investors precise as confirmation signal, create an excess optimism and push prices upward and generate low subsequent returns.

Table 3.5 examines whether analyst recommendations to 'Buy' are more pronounced for stocks with short-sale constraints and whether this contributes to momentum profits. This section performs a two dimensional analysis. First, the stocks are grouped into three portfolios based on their previous quarter's RIO. Second, stocks in each RIO portfolio are then grouped again into three portfolios on their analyst recommendation (Rec) into 'Buy', 'Hold' and 'Sell' recommendations prior to the formation period (*t*-7 to *t*-2). Finally, stocks within each element of the matrix (RIO x Rec) are then allocated into three further portfolios on the basis of their return performance during the formation period (*t*-7 to *t*-2). Portfolio P1 contains the worst performing 30 per cent stocks, P2 includes the middle 40 per cent stocks, and P3 includes the best performing 30 per cent stocks. The holding period (*t* to *t*+5) returns (raw) of these portfolios are reported in Table 3.5.

The results reconfirm that momentum profits are mostly concentrated within the lowest RIO portfolios of loser stocks. Table 3.5 further reveals that for each RIO portfolio, momentum returns decline monotonically from 'Buy' to 'Sell' recommendations. These results show that investors might be initially optimistic, when they receive a buy signal from analyst recommendation, they become more confident and push prices up, stocks become overvalued and subsequent returns are low, resulting in momentum profits generated by the return continuation on loser stocks.

Table 3.5 Momentum Returns by Short-sale Constraint and Analyst Recommendation

Average monthly raw returns (per cent) of portfolios composed on short-sale constraints and analysts' recommendation are reported. Short-sale constraint is measured by RIO, the residual of equation (3.2). Analyst recommendation on each stock is collected from I/B/E/S. First, at the end of each month *t*, all stocks are allocated into three RIO portfolios. Second, stocks in each RIO portfolios are grouped into three further portfolios on analyst recommendation (Rec) including 'Buy', 'Hold', and 'Sell' groups. All stocks belonging to each element of the (RIO x Rec) matrix are then grouped into three portfolios. The portfolios are P1 (the worst performing 30 per cent), P2 (the middle 40 per cent), and P3 (the best performing 30 per cent). The position is held for six-months (*t* to *t*+5). All portfolios are equally weighted. *T*-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) per cent level. The sample period is January 1993 to December 2002.

	Analyst Recommendation (Rec)			
RIO Portfolios	**Buy**	**Hold**	**Sell**	**Buy – Sell**
RIO1 (Low)	P3 – P1 = 2.46 (3.65*)	P3 – P1 = 2.01 (3.95*)	P3 – P1 = 0.72 (1.18)	P3 – P1 = 1.74 (2.25*)
RIO2	P3 – P1 = 1.89 (3.34*)	P3 – P1 = 0.79 (1.73**)	P3 – P1 = 0.86 (2.02**)	P3 – P1 = 1.02 (1.84**)
RIO3 (High)	P3 – P1 = 1.23 (1.94**)	P3 – P1 = 1.16 (2.63*)	P3 – P1 = 0.44 (0.83)	P3 – P1 = 0.79 (1.23)
RIO3 – RIO1	P3 – P1 = 1.23 (1.80**)	P3 – P1 = 0.84 (1.47)	P3 – P1 = 0.27 (0.38)	

To examine whether momentum profits are concentrated in stocks with high short-sale constraints and with analyst forecast revision upward, Table 3.6 performs a two dimensional analysis. First, the stocks are grouped into three portfolios based on their previous quarter's RIO. Second, stocks in each RIO portfolio are then grouped again into three portfolios on their analyst forecast revision (FRev) into 'Up', 'No change' and 'Down' revisions prior to the formation period (*t*-7 to *t*-2). Finally, stocks within each element of the matrix (RIO x FRev) are then allocated into three further portfolios on the basis of their return performance during the formation period (*t*-7 to *t*-2). Portfolio P1 contains the worst performing 30 per cent of stocks, P2 includes the middle 40 per cent of stocks, and P3 includes the best performing 30 per cent of stocks. The holding period (*t* to *t*+5) returns (raw) of these portfolios are reported in Table 3.6.

The results show that momentum profits are concentrated on loser stocks within the lowest RIO portfolios and analyst forecast revision upward portfolios. For each RIO portfolio, momentum returns decline monotonically from forecast revision 'Up' to 'Down'. The findings suggest that investors are initially optimistic, when they receive a forecast revision upward signal, they become overconfident and push prices up, stocks become overvalued and subsequent returns are low, resulting in momentum profits generated by the return continuation on loser stocks.

Table 3.6 Momentum Returns by Short-sale Constraint and Analyst Forecast Revision
Average monthly raw returns (per cent) of portfolios composed on short-sale constraints and analysts' recommendation are reported. Short-sale constraint is measured by RIO, the residual of equation (3.2). Analyst forecast revision on each stock is collected from I/B/E/S. First, at the end of each month *t*, all stocks are allocated into three RIO portfolios. Second, stocks in each RIO portfolios are grouped into three further portfolios on analyst forecast revision (FRev) includes 'Up', 'No change' and 'Down' groups. All stocks belonging to each element of the (RIO x FRev) matrix are then grouped into three portfolios. The portfolios are P1 (the worst performing 30 per cent), P2 (the middle 40 per cent), and P3 (the best performing 30 per cent). The position is held for six-months (*t* to *t*+5). All portfolios are equally weighted. *T*-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10) per cent level. The sample period is January 1993 to December 2002.

	Analyst Forecast Revision (FRev)			
RIO Portfolios	**Up**	**No Change**	**Down**	**Up – Down**
RIO1 (Low)	P3 – P1 = 2.24 (4.11*)	P3 – P1 = 1.83 (3.71*)	P3 – P1 = 1.06 (2.21*)	P3 – P1 = 1.18 (1.91**)
RIO2	P3 – P1 = 1.61 (3.76*)	P3 – P1 = 1.21 (2.65*)	P3 – P1 = 1.05 (2.60*)	P3 – P1 = 0.56 (1.18)
RIO3 (High)	P3 – P1 = 1.17 (2.75*)	P3 – P1 = 1.55 (3.20*)	P3 – P1 = 0.88 (1.67**)	P3 – P1 = 0.28 (0.52)
RIO3 – RIO1	P3 – P1 = 1.06 (1.90**)	P3 – P1 = 0.28 (0.54)	P3 – P1 = 0.16 (0.27)	

Overall, the findings of this section are consistent with the prediction that return continuation on loser stocks will be most pronounced with low institutional ownership (high short-sale constraints) and public good signals. The results show that stocks with high past returns, analyst recommendations to buy, and analysts revising their forecast upward provide an environment in which unsophisticated investors accelerate their confidence level, this might lead to excessive optimism about the firm and subsequent momentum profits.

Since the previous sections find that the profitability of momentum strategies are driven almost entirely by the loser stocks, it will be interesting to see what happens to these loser stocks in pre- and post-formation periods. Figures 3.2 and 3.3 plot the cumulative raw returns and mean monthly returns of loser portfolios under five quintile groups of residual institutional ownership respectively, in the 12-month prior to formation period (*t*-17 to *t*-7), formation period (*t*-7 to *t*-2), and 24-month holding period (*t*-1 to *t*+23). The results show that positive returns could be earned in the 12-month prior to formation period only at the lowest RIO quintile and slight positive returns for RIO2. Given that the earlier results show that momentum profits can only be observed from the lowest two RIO quintiles, the results in this section thus indicate that loser stocks under short sales constraints are initially overpriced. Together, the 24-month holding periods show that the market eventually corrects the mispricings. This is consistent with behavioural models by Daniel et al. (1998) and Hong and Stein (1999) that momentum is initially an over reaction and is followed by a long-run reversal. Yet, Figure 3.2 and 3.3 show that the overreaction theory does not fully explain the long-run anomaly. There is strong long-run reversal in all RIO quintiles despite there being no early momentum. This finding is in line with Cooper et al's. (2003) finding that long-run reversal can appear without short-run momentum.

Figure 3.2 Cumulative momentum returns of loser portfolios under five quintile groups of residual institutional ownership

At the end of each month *t*, all stocks are allocated into quintile based on their six-month formation-period from *t*-7 to *t*-2 and by the end of the previous quarter residual institutional ownership (RIO). RIO is obtained from a cross-sectional regression using eq.2. Quintile portfolios are formed monthly by weighting equally all firms in that quintile ranking. The figure shows the cumulative returns of loser portfolios under five quintile groups of residual institutional ownership. The time scale is 12-month prior formation period (1-12), formation period (13-18), and 24-month post formation period (19-42).

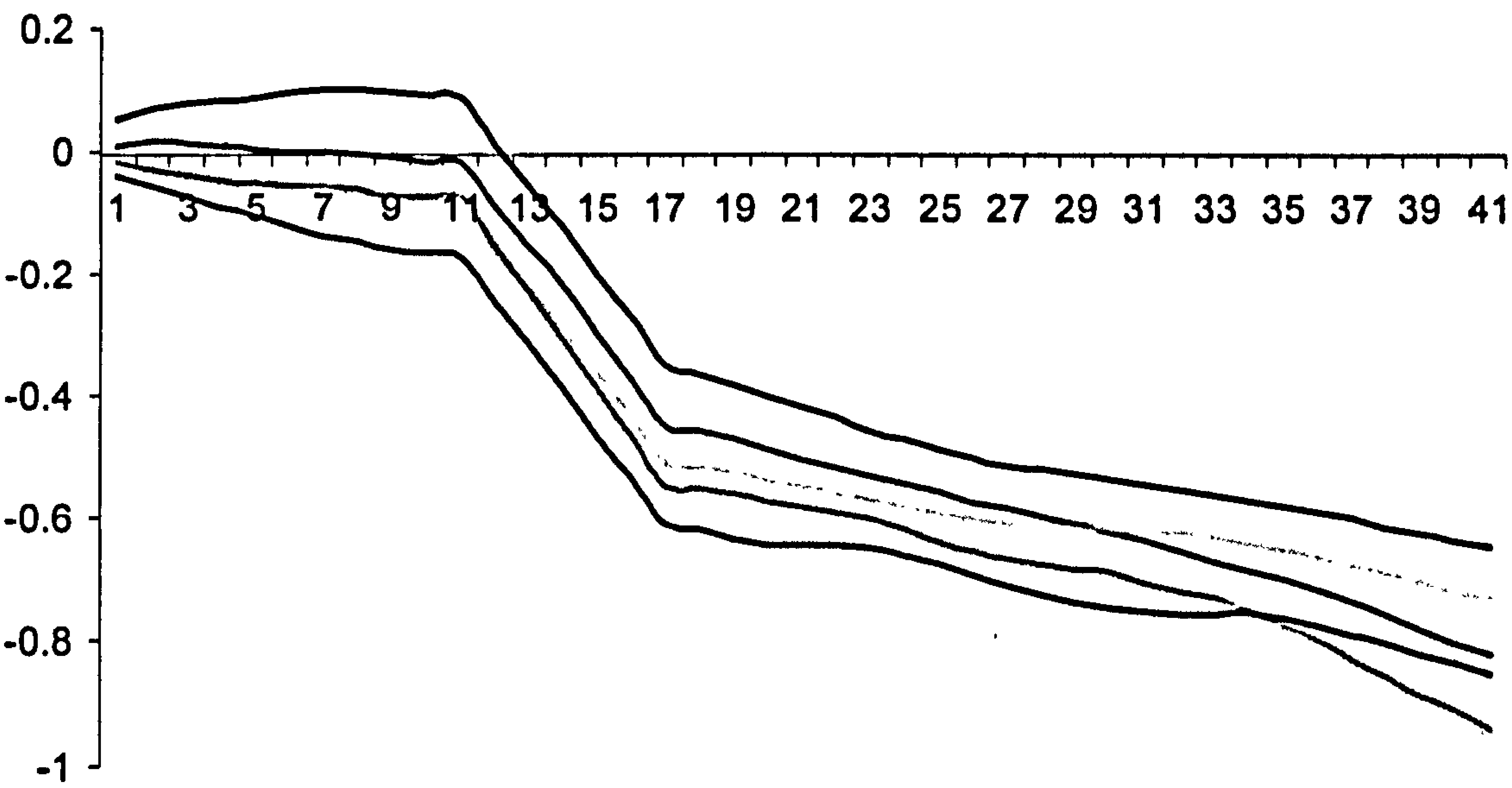
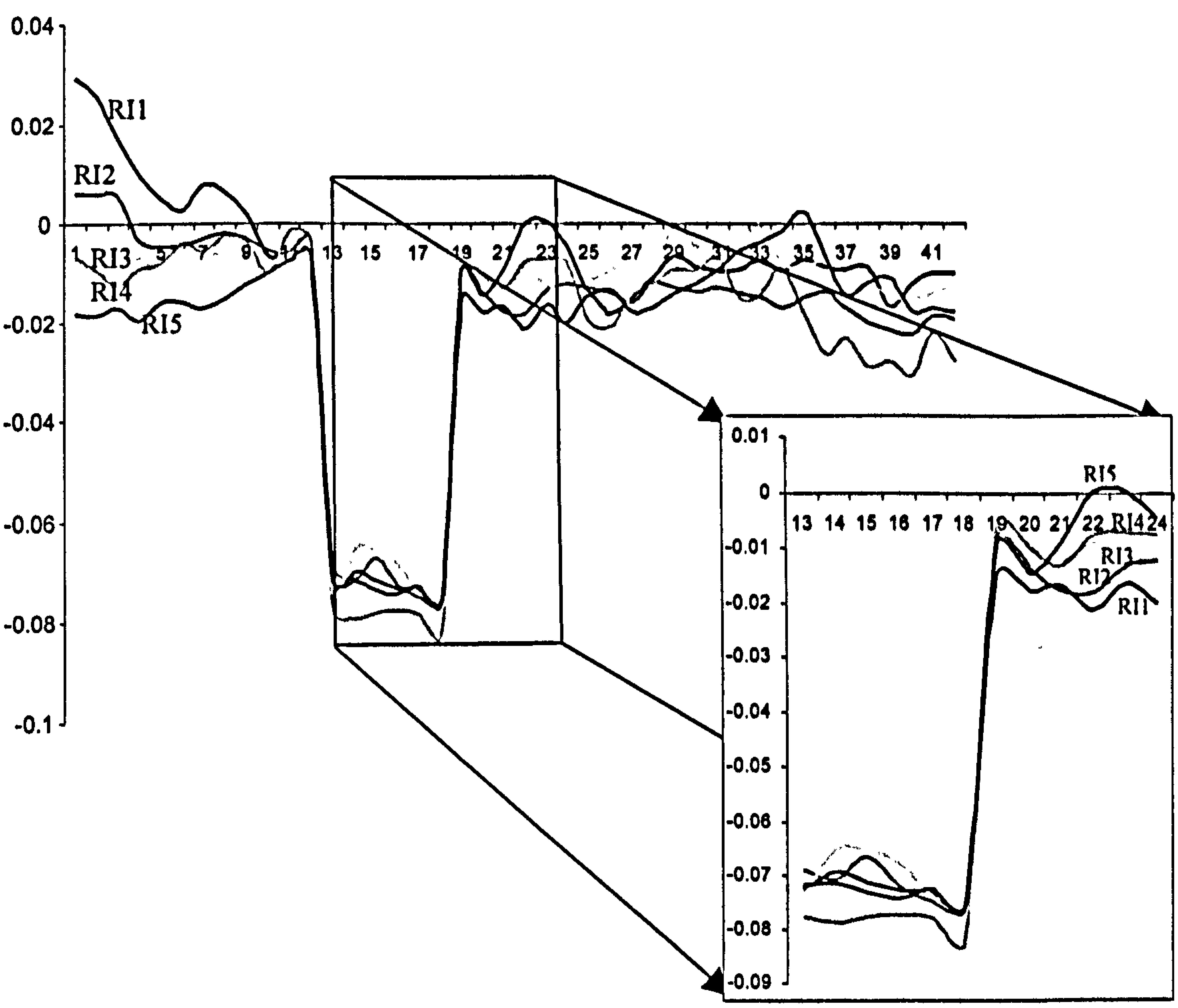


Figure 3.3 Mean monthly returns of loser portfolios under five quintile groups of residual institutional ownership

At the end of each month *t*, all stocks are allocated into quintile based on their six-month formation-period from *t*-7 to *t*-2 and by the end of the previous quarter residual institutional ownership (RIO). RIO is obtained from a cross-sectional regression using eq.2. Quintile portfolios are formed monthly by weighting equally all firms in that quintile ranking. The figure shows the mean monthly returns of loser portfolios under five quintile groups of residual institutional ownership. The time scale is 12-month prior formation period (1-12), formation period (13-18), and 24-month post formation period (19-42).



3.6 Cross-sectional regressions

To examine the interaction between momentum profits and the previously identified momentum-related factors, this section conducts a series of cross-sectional regressions. This allows us to explore the above interrelationships while controlling for the predictors.

It also serves as a robustness check on the methodology of two/three dimensional analysis applied in previous sections.

Cross-sectional regressions are estimated for each month *t* from January 1993 to December 2002. The coefficient estimates reported in Table 3.7 are the time-series averages of the monthly estimates. The dependent variable is the average monthly return over the six-months holding periods subsequent to the current month *t*. Explanatory variables are RIO, Prior return, Disp, Rec and FRev, as defined earlier. The t-statistics are based on the Newey-West autocorrelation consistent standard errors.

In Table 3.7 (Model 1), the average monthly returns over the six-month holding periods (*t* to *t+5*) are regressed on prior returns over the six-month formation period (*t*-7 to *t*-2) and RIO. The coefficient estimates are consistent with the earlier portfolio results suggesting the presence of momentum returns, and the strong negative relationship between momentum and residual institutional ownership.

In Model 2, the average monthly returns over the six-month holding periods (*t* to *t+5*) are regressed on prior returns over the six-month formation period (*t*-7 to *t*-2), RIO and Disp. The coefficient on RIO is -0.019 (t-statistic -2.10) and the coefficient on Disp is -0.021 (t-statistic -0.92) confirming the previous results that momentum profits are most pronounced for both short-sale constraints but are not linked to divergence in opinions.

Model 3 and model 4 look at the effect of analyst recommendation and analyst forecast revision in isolation and at its interaction with RIO and prior returns. The results show that momentum profits are strong in all cases. The findings continuous to establish the negative relationship between momentum and institutional ownership in both models. In addition, the findings suggest that momentum profits might link to overconfidence and self attribution bias.

In Model 5, the average monthly returns over the six-months holding periods (*t* to *t+5*) are regressed on prior returns over the six-months formation period (*t*-7 to *t*-2), RIO, Disp, Rec and FRev. The results show that each of these variables contain strong effects on future returns, except Disp, which measure for divergence in opinion.

Table 3.7 Cross-sectional regression analysis

This table shows average monthly regression coefficients from January 1993 to December 2002. The dependent variable is the average monthly return over the six-month holding periods subsequent to the current month t. RIO is the residual institutional ownership obtained from a cross-sectional regression using eq.2. VO is the three-month period trading volume prior to the first day of the formation period (t-7 to t-2). Prior return is the average monthly returns over the six months prior to the current month t. Disp is the three-month period of analysts' forecasts dispersion prior to the first day of the formation period. Rec is the analyst recommendation. FRev is the analyst forecast revision. t-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *(**) Denotes significance at the 5(10)% level. R^2 is the time-series average of the monthly adjusted R^2.

	Model				
	1	2	3	4	5
Intercept	-0.008 (-1.82**)	-0.005 (-1.11)	-0.007 (-1.28)	-0.004 (-1.22)	0.001 (0.22)
RIO	-0.012 (-1.76**)	-0.019 (-2.10*)	-0.015 (-2.15*)	-0.014 (-2.14*)	-0.016 (-2.29*)
Prior return	0.122 (4.80*)	0.105 (4.21*)	0.188 (6.41*)	0.181 (5.72*)	0.242 (3.22*)
Disp		-0.021 (-0.92)			0.006 (0.43)
Rec			0.001 (1.65**)		0.006 (2.00*)
FRev				0.001 (2.48*)	0.002 (2.43*)
Adj R^2(%)	2.86	6.68	5.66	6.06	21.32

3.7 Short sales constraints and the value premium

The previous section has established the strong link between momentum profits and short-sale constraints. It will be interesting to see if other zero-sum investment strategies based on the value premium/book-to-market effect will also display such a pattern in the UK. First, this section sorts all stocks into quintiles at the end of each month t based on their returns during the six month formation period (t-7 to t-2). This section then groups the stocks of each book-to-market category into five portfolios (equal stocks) on previous quarter's RIO obtained from equation (3.2).

The results in Table 3.8 support the views that the value premium is most pronounced in low B/M stocks with high short-sale constraints. The average difference between the monthly returns of BM5 and BM1 portfolios in the lowest RIO quintile is 2.09 per cent (T-statistic = 5.66). In contrast, the differences between returns of BM5 and BM1 in RIO5 portfolios are statistically insignificant. The results also show that almost all of the contribution to momentum profits comes from low B/M stocks. The findings are very similar to those of the momentum anomaly that this chapter has established earlier. In addition, the results are consistent with Nagel (2005) that the book-to-market effect is primarily concentrated in stocks that are difficult to short.

Table 3.8 Mean Monthly Portfolio Returns by Residual Institutional Ownership and Book-to-Market Effect

At the end of each month t, all stocks are allocated into quintile based on their book-to-market ratio (B/M) at time t and by the end of the previous quarter residual institutional ownership (RIO). Decile portfolios are formed monthly by weighting equally all firms in that decile ranking. The position is held for the following twelve-month period (t to t +11). This table reports the strategy's mean raw returns during the holding period. t-statistics (in parentheses) are based on Newey-West autocorrelation consistent standard errors. *denotes significance at the 5% level. The sample period is January 1993 to December 2002.

	Residual Institutional Ownership (RIO)					
Book-to-Market	**RIO1 (Low)**	**RIO2**	**RIO3**	**RIO4**	**RIO5 (High)**	**RIO5 - RIO1**
BM1 (Low)	-1.82	-1.75	-1.32	-0.75	-0.49	1.33 (2.87*)
BM2	-0.89	-1.03	-0.89	-0.80	-0.70	0.19 (0.68)
BM3	-0.73	-0.60	-0.71	-0.60	-0.39	0.35 (1.94)
BM4	-0.28	-0.48	-0.16	-0.21	-0.25	0.03 (0.18)
BM5 (High)	0.27	0.11	0.40	0.21	0.08	-0.18 (-1.14)
BM5 – BM1	2.09 (5.66*)	1.86 (5.52*)	1.72 (5.60*)	0.96 (2.99*)	0.57 (1.75)	-1.52 (-3.34*)

3.8 Conclusions

Extensive evidence on the persistence of momentum profits has challenged the rational expectation-based predictions of modern finance theory, yet its causes and exploitability are unknown. To fill this gap, this chapter examined three issues. They are: (a) what are the possible sources of momentum profits? (b) to what extent are momentum profits linked to overconfidence, limits to arbitrage and divergence in opinion? and (c) are momentum profits exploitable? More specifically, following the predictions of Miller (1977) this chapter examines whether stocks characterised with limits to arbitrage and high divergence in investors' beliefs contribute to momentum profits. Several conclusions emerge.

This chapter finds that momentum profits come from loser stocks. There is strong evidence of a positive relationship between short-sale constraints and the magnitude of momentum profits. The known risk factors cannot explain the momentum profits. However, the results are inconsistent with Miller's (1977) view that stocks that are subject to both short-sale constraints and high divergence in opinion are initially overvalued and generate low subsequent returns. This chapter find that momentum profits might be linked with short sale constraints but not with divergence in opinion. On the other hand, excessive optimism together with self attribution bias leading to overvaluation and therefore low subsequent returns better explain momentum profits.

The findings of this chapter have several implications. First, momentum profits might not be exploitable easily as these are generated primarily by loser stocks that are costly or impossible to sell short. Second, the investors' inability to short-sell loser stocks defeats the original theme of momentum trading that argues for a self-financing hedge portfolio. Third, the persistence in momentum profits might be caused by limits to arbitrage rather than investors under-reacting to firm-specific information. Finally, the results support the view that momentum profit results primarily from mispricing due to limits to arbitrage and overconfidence, while divergence in opinion does not play a role in overvaluation.

4. Analyst Bias, Uncertainty and Momentum Profits

4.1 Introduction

There is overwhelming empirical evidence documenting the apparent success of the momentum strategy where buying stocks with high returns over the previous 3 to 12 months and selling stocks with poor performance over the same period of time can generate significant abnormal returns over a medium holding period. The apparent momentum in stock prices appears to be strong in the US and Europe and to a lesser extent in Asia. Griffin, Ji, and Martin (2003) document that 17 of the 40 countries they studied display positive and significant momentum profits. In addition, they found that momentum profits for Asia are substantially weaker than those around the world, particularly to Europe. Similarly, Rouwenhorst (1999) found weaker momentum profits for emerging markets. In addition, Chui, Titman, and Wei (2003) found that the momentum effect is generally weak in Asian countries. Although the literature has reached a consensus on the existence of momentum in stock prices, there is still no consensus on the source(s) of momentum profits.

Previous works based on behavioural theories attempted to explain the payoff of momentum strategies. Daniel et al. (1998) and Hong and Stein (1999), each employing different behavioural or cognitive biases, suggest that over-reaction is the source of momentum profits. Barberis et al (BSV, 1998) and Zhang (2006) suggest that investors under-react to new information and stock prices continue to move in the same direction. According to behavioural theories, stocks that are small, have less available information on fundamentals, fewer investors/analysts to follow their progress, whose businesses are hard to value, implementation costs are high and arbitrage rather limited should exhibit higher momentum. However, the extant behavioural finance literature has not yet been able to provide a unifying 统一·使一元化 explanation to momentum profits. In addition, there are few attempts to search for behavioural explanations for momentum profits across countries. This chapter fills this gap

The hypothesis of this chapter is based on works in the behavioural economics and finance literature. Jiang, Lee and Zhang (2005) and Zhang (2006), using information uncertainty variables as proxied by firm size, firm age, analyst forecast dispersion, leverage, return volatility, and cash flow volatility, show that momentum profits are linked with information uncertainty. In particular, Zhang (2006) shows that greater information uncertainty leads to relatively lower future stock returns following bad news and relatively higher future returns following good news, indicating that uncertainty prevents timely information incorporation into stock prices. Gentzkow and Shapiro (2006) propose a model of media bias that suggests that a media firm with a reputation concern will distort information in order to conform with consumers' prior beliefs whenever the outcomes are difficult to observe.

This chapter combines these two ideas and develops the hypothesis: if the momentum profits are linked to uncertainty, in particular, higher momentum profits when there is higher uncertainty and if investors are unable to gain access to their own source of information, their information set will be reliant on their agents i.e. analysts. Analysts who are concerned for their reputations will act on or reveal information depending on their clients' prior beliefs whenever possible in order to maximize their rewards. In sum, when there is more uncertainty, hence, when the true information is difficult to observe, analysts make earnings forecasts and recommendations that bias towards their client's desire, i.e. release positive news for winners stocks pushing prices upward and distort negative news for loser stocks pushing prices downward. As a result, momentum profits should be high when uncertainty and analyst bias are high.

Risk factors are commonly used to explain the market anomaly, however, Fama and French (1996) concede that momentum trading is the only CAPM-related anomaly that their three-factor model fails to explain. In addition, the extant literature has not yet been able to identify any appropriate risk factors that might explain the momentum anomaly. Recently, Chordia and Shivakumar (2002) showed that momentum profits are linked with the business cycle. Avramov and Chordia (2006) suggest that although business cycle risk is captured by Treasury Bill yield, the term spread, and the default spread do not directly explain momentum profits, however, the sources of momentum profits can be traced to undiscovered risk factors associated with the business cycle pattern. Antoniou, Lam and Paudyal (2007) find similar results for European stock markets. Naranjo and Porter (2004) document that country-neutral momentum returns are significantly correlated across countries and are time-varying. Their results are in line with the notion that momentum strategies are exposed to some common yet unidentified price risk factor.

Given that credit risk varies over the business cycle, Avramov, Chordia, Jostova and Philipov (2007) show that momentum profits are linked with credit rating. Their cross-sectional results show that momentum profits are concentrated on high credit risk firms only[35]. However, the time-series findings show that momentum profits are higher during expansionary periods where credit risks should be lower than those during recessionary periods. As a result, the inconsistency between the time-series and cross-sectional findings suggest that momentum profit is not a compensation for credit risks. This chapter attempts to examine the link between credit rating and momentum profits further by incorporating analyst bias.

Using a sample of 22033 stocks covering 41 countries over the periods from 1983 to 2002 for the US, and from 1987 to 2002 for the rest of the world, this chapter finds that, consistent with the existing literature, momentum strategies are largely profitable on average around the world, and momentum profits for Asia are distinctly weaker than for Europe. In addition, the findings suggest that stocks with I/B/E/S coverage earn higher momentum profits than stocks that are not covered. The results show that the sample of I/B/E/S coverage firms is representative.

Trading strategies conditional on three dispersion of analyst forecast (Disp) and three prior six month return groups yield momentum payoffs that increase monotonically with the dispersion of analyst forecast across countries. The results are more pronounced for countries that have experienced momentum payoffs. Similarly, based on three uncertainty

[35] Avramov and Hore (2008) build a theoretical model show that momentum profits exist in high information uncertainty and high credit risk stocks, suggest that the combination of leverage, which proxies for credit risk and information uncertainty, which represents risky cash flow firms could generate risk factors that could explain the momentum profits.

(V) and three past return portfolios, momentum payoffs increase monotonically with uncertainty. On the other hand, based on three diversity of analyst forecast (1-ρ) and three past return groups, the momentum profits drop monotonically with increase in diversity of analyst forecast, suggesting that momentum profits are stronger with higher agreement/consensus among investors. In addition, within each of the uncertainty groups, the extreme winner and loser portfolios are among higher analyst bias groups. The findings suggests that analysts with reputational concerns report forecasts in accord with client's beliefs, hence greater analyst bias when there is greater uncertainty. The extreme winner and loser stocks continue to move in the same directions reflecting investors' beliefs promoted by analyst bias rather than the true set of information.

This chapter also examines the link between credit rating, analyst bias and momentum profits in the US[36]. The results show that momentum profits are concentrated among high credit risks and high analyst bias firms during expansionary periods, and loser stocks are the dominant source of the profitability of momentum strategies. The findings suggest that analysts with reputation concern report earnings forecasts in accord with the client's desire and distort bad news for the poorest credit quality firms whenever the outcomes are difficult to detect and/or mistakes are less painful to absorb i.e. during expansionary periods. During recessionary periods, however, analysts will choose to forecast earnings close to if not the same as the consensus forecast since mistakes are more costly and painful.

Finally, the chapter reports a head-to-head comparison of a strategy that based on uncertainty, by buying low uncertainty winners and selling high uncertainty losers, with the traditional Jegadeesh-Titman momentum strategy. The findings show that the uncertainty momentum strategy is superior to the Jegadeesh-Titman momentum strategy. 34 of 41 countries display momentum profits for uncertainty momentum strategy compared to 24 of 41 countries for the Jegadeesh-Titman momentum strategy.

[36] Due to lack of data available for the credit rating by S&P of other countries, this chapter only examines the effect on US Data.

This chapter makes several contributions to the behavioural economics and finance literature. First, this chapter establishes a strong link between uncertainty and momentum profits across countries. Second, the findings report that greater uncertainty with greater analyst bias leads to negative returns for loser stocks, and hence greater momentum profits. As a result, the momentum effects are more likely to reflect slow absorption of ambiguous information into stock price because analysts with reputational concerns report forecasts in accord with client's beliefs rather than the true set of information. The findings provide empirical evidence for the economic theory of 'herding on the priors' and reputational effects in sender-receiver games[37], as well as the finance literature on the sources of momentum profits. Third, this chapter provides evidence on global data that analysts' forecast dispersion reflects uncertainty rather than disagreement, consistent with Johnson (2004)[38]. Fourth, the chapter suggests that the strong link between credit rating and momentum profits in the US documented by Avramov, Chordia, Jostova and Philipov (2007) can be explained by analyst bias. Finally, the chapter finds that profits from a momentum strategy based on uncertainty, by buying low uncertainty winners and selling high uncertainty losers, are greater (includes most Asian countries) than the Jegadeesh-Titman momentum strategy.

The remainder of the chapter is organized as follows. Section 4.2discusses the related literature and develops the testable hypotheses. Section 4.3 discusses the sample data and methodology. Section 4.4 presents the empirical results. Section 4.5 concludes the chapter.

4.2 Related Literature and Hypotheses Development

4.2.1 *Risk and uncertainty*

Conventional finance theory assumes complete agreement among investors about the probability distribution of future payoffs on assets. As a result, investors will accurately process all available information about the distribution of future payoffs and have

[37] For the related literature on 'herding on the priors' and reputational effects in sender-receiver games, see Gentzkow and Shapiro (2006).

[38] Johnson (2004) suggests that the negative relation between dispersion in analysts' forecast and future returns may be due to the uncertainty (or risk) reflecting in dispersion, the option value of the firm increase and result in low subsequent returns.

complete knowledge of the distribution. In other words, the future stock return payoff is known with certainty. In reality, however, investors are uncertain about the true probability structure of stock return payoffs. Consequently, uncertainty about the future stock returns payoffs could influence asset prices. In particular, Knight (1921) makes a distinction between risk and uncertainty. Risk exists when a probability based on past experience can be attached to an event, whereas uncertainty exists when there is no objective way to place a probability on an event. More importantly, he argues that investors dislike uncertainty more than risk. As a result, investors will show an extra aversion to uncertainty beyond their aversion to risk. Ellsberg (1961) shows that individuals may prefer to gamble with precise probabilities, hence risk, than to gamble with unknown odds, hence uncertainty. Rigotti and Shannon (2005) suggest that high uncertainty stops some assets being traded due to uncertainty aversion. The distinction between uncertainty and risk suggests that while higher risk is associated with higher expected returns, higher uncertainty could be associated with lower expected returns.

4.2.2 *Measures of uncertainty and disagreement*

Using dispersion of analyst's earnings forecasts to proxy for divergence of opinion, Diether, Malloy and Scherbina (2002), hereafter DMS (2002), found that stocks with higher dispersion in analyst's earnings forecasts tend to have lower future stocks market returns. They suggest that because the marginal investor fails to fully account for the correlation between analyst disagreement and forecast bias, high dispersion stocks are likely to be overvalued and to underperform otherwise similar stocks in the future. Another reason why increased dispersion of beliefs should be associated with lower prices comes from the fact that uncertainty aversion should generally increase with belief dispersion; that is, the fact that different investors more strongly disagree about subjective probabilities attached to some states is indicative of a greater difficulty of estimating these probabilities, and hence of greater uncertainty. Then, because of uncertainty aversion, the market prices for claims to states should be lower with greater dispersion of beliefs. Since the current findings as to whether dispersion in analysts' forecast captures the nature of disagreement or uncertainty are not conclusive, it is ultimately an empirical question.

Baron, Kim, Lim and Stevens (1998), hereafter BKLS (1998), argue that dispersion in analysts' forecasts is likely to be a poor proxy for investor disagreement. Along this line, Doukas et al. (2006) found that the negative relation between dispersion in analysts' forecasts and ex-post stock returns documented by DMS (2002) were reversed once they controlled for uncertainty in analysts' earnings forecasts.

BKLS argue that forecast dispersion reflects both the degree of non-redundancy in individual analysts' information and the lack of precision of individual analysts' forecast. The BKLS uncertainty and diversity in analysts' forecast can be measured as follows:

$$\textit{Dispersion (Disp)} = V(1-\rho) \tag{4.1}$$

$$\textit{Consensus} = \rho = 1\text{-}Disp/V \tag{4.2}$$

$$\textit{Diversity (Disagreement)} = (1-\rho) \tag{4.3}$$

Where, Disp is dispersion in analysts' forecasts[39], i.e., the sample variance of the individual forecasts (FC_i) around the mean forecast ($\overline{FC}$), measured as $\sum_{i=1}^{n}(FC_i-\overline{FC})^2/(n-1)$, where n is the number of forecasts. ρ is consensus, V is uncertainty, i.e., the mean of the squared differences between individual analysts' forecasts (FC_i) and reported earnings per share (EPS) measured as $\sum_{i=1}^{n}(FC_i-EPS)^2/n$.[40]

If DMS' demonstration that stocks with higher dispersion in analysts' earnings forecast earn significantly lower future returns that otherwise similar stocks is correct, and if BKLS's argument on dispersion in analysts' forecast captures uncertainty is also correct, the combined effects suggest the testable proposition as follows.

Hypothesis 1: the higher the uncertainty, the lower the future returns for loser stocks and

[39] It is also a product of uncertainty (V) and diversity in analysts' forecasts (1-ρ)

[40] The relations this chapter reports between dispersion, consensus, and uncertainty are not merely mechanical. Theoretically, which component, V or (1-ρ), has more explanatory power for dispersion is, *ex ante*, not clear (Barron et al. 1998). Also see Section 4.3 for empirical evidence that this relation is not merely mechanical.

hence the higher the momentum profits.

4.2.3 *Behavioural Theories*

Daniel et al. (DHS, 1998) suggest investor overconfidence causes over-reaction and generates momentum, the over-reaction in prices will eventually be corrected in the long run as investors observe future news and realize their error. As a result, increased overconfidence generates momentum in the short run and reversal in the long run. Hong and Stein (HS, 1999) argue that private information diffuses only gradually through the marketplace leading to an initial under-reaction to news; subsequently positive serial correlation in returns attracts the attention of the momentum traders who trade actively and over-react. Eventually, prices revert back to their fundamental levels. Hong, Lim, and Stein (2000) test the HS model and found that the diffusion of information is lower for momentum stocks.

The under-reaction hypothesis has also been used to explain the momentum anomaly. Barberis et al (BSV, 1998) show that investors are subject to a conservatism bias which causes them to under-react to earnings and other corporate news, causing short-run positive autocorrelation, but when they observe trends of earnings rising, the positive signal causes them to switch to over-reaction, causing long-run negative autocorrelation. Zhang (2006), based on the under-reaction hypothesis, argues that momentum effects are more likely to reflect slow absorption of ambiguous information into stock price than reflect missing risk factors; such under-reaction prevents timely new information being incorporated into stock prices.

Another common corollary of behavioural theories is that momentum could be the result of mispricing, such that overpriced stocks earn predictably low future returns and underpriced stocks earn predictably high returns. Ali and Trombley (2006) found that momentum profits are positively related to short sales constraints, suggesting that the persistence of momentum profits may be due to the fact that arbitrage is costly and any systematic mispricing would not be traded away quickly and completely in situations where arbitrage costs exceed arbitrage benefits.

4.2.4 *Analyst Bias*

A Bayesian consumer who is uncertain about the quality of an information source will infer that the source is of higher quality when its reports conform to the consumer's prior expectations. (Gentzkow and Shapiro, 2006, JPE)

Based on the above statement, Gentzkow and Shapiro (2006) developed a new model of media bias. The model is based on the assumption that in order to build a reputation for a media firm, it will distort information to make it conform to consumers' prior beliefs rather than report true information or the true belief/opinion of the firm. Such behaviour is motivated by the fact that consumers always want to receive confirmation of their priors from the third party. However, the incentives to distort information from a media firm drop when the true state of the world becomes easier to observe. In other words, a media firm will choose to report information close to the truth rather than in accord with consumers' beliefs if the outcomes are soon to be observable. In addition, the model predicts that competition can reduce media bias.

Since analysts care about reputation as much as media firms do, this chapter applies the media bias model to test if analysts are more likely to distort information and predict earnings in favour of his client's priors when the actual earnings are difficult or immediately observable. In addition, the model assumes that bias is most severe when clients are at their most uncertain about the future prospects of a company.

The media bias model argues that the two key elements to determine the strength and direction of bias are feedback and competition. Feedback has an inverse relationship with bias. When feedback is immediate i.e. the truth is easily and quickly observable, media firms need to make sure that their reports are close to if not the same as to the outcome. Applying this to analyst bias suggests that when an earnings announcement is approaching, analysts tend to forecast earnings very close to if not the same as the actual earnings i.e. the forecast error will be low. On the other hand, analysts will make their forecast close to their client's belief when the publication of the forecast is some time away from the earnings announcement. The model suggests that competition also has an inverse relationship with bias. The more analysts who follow a firm, the more difficult/costly it is for an analyst to report an at odds forecast, as a result, competition reduces the forecast error. This chapter measures analyst bias as follows:

Prior to the end of the fiscal year

$$AB_{j,t} = | F_{j,t} - A_{j,t} | / SD_{j,t} \quad (4.4)$$

where: $AB_{j,t}$ = Analyst bias of stock j at time t

$F_{j,t}$ = Mean forecast prior to cutoff date

$A_{j,t}$ = Actual earnings per share for stock j

$SD_{j,t}$ = Standard deviation of earnings forecast

Analyst bias is measured as the absolute forecast error, computed as the absolute value of the difference between mean forecast and actual EPS, and deflated by the standard deviation of analyst forecast. The absolute forecast error captures the feedback from the media bias model and the standard deviation of earnings forecast captures the feedback. As a result, the equilibrium analyst bias is high when forecast error is high (feedback is high) and the standard deviation is low (competition is high).

Traditional interpretations on optimistic earnings forecasts tend to be that analysts want to win favour with firms and therefore be able to gain access to private information. Applying the media bias suggests that the bias does not arise from consumer choice for confirmatory information or analysts' incentives to express their own views. Instead, it is because analysts' desiring to build a reputation report forecast in accordance with their client's desire whenever the actual earnings are yet to be observed.

In the presence of uncertainty, the analyst bias could influence future returns of winner and loser stocks differently, analysts report an increase in earnings forecast and/or recommendation to buy winner stocks to meet their client's desire, and therefore stock prices continue to increase. On the other hand, analysts knowing that clients do not want to realize losses on loser stocks try not to report earnings decreases and/or recommendations to sell loser stocks. This chapter therefore formulates the hypothesis as follows:

Hypothesis 2: Expected momentum profits are high when uncertainty and analyst bias are high.

4.2.5 *Credit rating in the US*

Avramov, Chordia, Jostova and Philipov (2007) suggest that momentum profits that are mainly contributed by loser stocks are concentrated among the highest credit risk firms. However, previous empirical evidence also suggests that momentum profits are high during expansion periods, when credit risks are generally lower than during recessionary periods. To illustrate, Figure 4.1 shows the credit risk where 4 is the highest and 1 is the lowest.

Figure 4.1 The disagreement between time-series and cross-sectional analysis

Business cycle	Credit risk	
	High	Low
Expansion	3	1
Recession	4	2

The puzzle lies in the fact that momentum profits are concentrated on stocks with credit risk equal to 3 rather than 4. Analyst bias offers an explanation for this puzzle, since analyst bias suggest that analysts with reputation concern continue to find times when they can report forecast in accordance with clients' desire. Stocks with high default risks are harder to detect, or investors are feeling less vulnerable and mistakes are less painful to absorb during good periods and when the market is confident. Since the true status is harder to detect, analysts therefore choose to recommend to buy winner stocks and to hold loser stocks, since investors want to realize gains but not to realize losses.

4.3 Data and methods

4.3.1 Data Sources and Sample Selection

This section describes the data sources and the sample selection. Data on stock returns, market capitalisation and book to market value are from the Thomson Datastream (TDS) database. This chapter uses analyst forecasts information included in the Institutional Brokers Estimate System (I/B/E/S) Detail History dataset and Summary History datasets[41]. The sample of 22033 stocks covers 41 countries over the periods from 1983 to 2002 for the US[42], and from 1987 to 2002 for the rest of the world. This choice of sample has been guided by the availability of data from I/B/E/S. Only common and non-financial stocks are included. Results are reported in local currency returns.

For current companies, this chapter match between Datastream and I/B/E/S databases through the SEDOL code. For dead companies, this chapter manually match the two databases by the company name. Stocks that are covered by I/B/E/S and with available returns data from Datastream are classified as 'Stocks with I/B/E/S coverage'. Stocks that are not covered by I/B/E/S but with available returns data from Datastream are classified as 'Stocks without I/B/E/S coverage'.

Since a reasonable number of stocks are needed to form momentum portfolios, this chapter required each country to have at least 30 stocks that meet the stock selection criteria in any month during the sample period. Furthermore, this chapter required each momentum portfolio in each country to have a return history of at least five years. Because of the last two criteria, the sample includes only forty-one countries, with a total of 22033 individual stocks.

Following Diether et al. (2002), this chapter computed month-end averages and standard deviations from the individual estimates in the Detail History file by extending each forecast until its revision date. For example, if the forecast was made in May and was last

[41] Note that although the I/B/E/S summary suffers the problems of rounding procedure (see Payne and Thomas (2003), the empirical results are qualitative unaffected

[42] Ince and Porter (2006) compare Datastream and CRSP datasets for US equities and show that after careful screening, inferences drawn from Datastream are similar to those drawn from CRSP, in particular for data from 1987 onward.

confirmed as accurate in July, it will be used in the computation of averages and standard deviations for May, June, and July. If an analyst makes more than one forecast in a given month, only the last forecast is used in the calculations. In some records, a revision date precedes the actual forecast date, which constitutes an error on the part of I/B/E/S. In this case, the forecast will be assumed to be valid only for the month in which it was made. This chapter deletes observations for which the absolute value of earnings forecast revision exceeds 100% of the prior year-end stock price. Analyst forecast data are adjusted for stock-split using the adjustment factor provided by Datastream.

4.3.2 Momentum strategies

For the computation of momentum strategies, this chapter follows the most widely reported results of the 6 x 6 strategy. For each month *t*, all stocks in each country are allocated into three portfolios based on their six-month formation-period from *t*-7 to *t*-2: Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30%, portfolio P2 contains the middle 40%, and portfolio P3 includes the best-performing 30%. The position is held for the following six-month period (*t* to *t*+5). This chapter employs one month gap between the formation and holding period to avoid the momentum effect with very short-term reversals and the bid-ask bounce effects established by previous studies (See Jegadeesh (1990), Jegadeesh and Titman (1995)). As in Jegadeesh and Titman (1993), to increase the power of the tests this chapter constructs overlapping momentum portfolios

4.3.3 Uncertainty and the Divergence of Opinion Measure

As argued by Baron, Kim, Lim and Stevens (1998) and proved by Doukas et al. (2006), the dispersion in analysts' forecasts is likely to be a poor proxy for investor disagreement since it is vitiated by the effects of uncertainty in individual forecasts about the future payoffs of stocks. As a result, using dispersion in analysts' earnings forecasts as a proxy for divergence of opinion to assess its relation with stocks returns and momentum profits could be erroneous. This chapter therefore uses the diversity measure of BKLS's (1-ρ) instead to proxy for divergence of opinion. BKLS show that forecast dispersion can be expressed as $D = V(1-\rho)$, where V is uncertainty and (1-ρ) is diversity (disagreement) in analysts information. Diversity of analyst forecast (1-ρ) is defined as one minus the consensus (i.e. the degree of common beliefs among analysts), measured by the correlation in forecast errors across analysts. In this case, unlike previous studies, this chapter uses V to measure the uncertainty and (1-p) the diversity measure as a true measure for divergence of opinion.

4.3.4 Credit Rating in the US

This section uses data stocks that are rated by Standard & Poor's Long-Term Domestic Issuer Crediting Rating on Compustat on a quarterly basis. This chapter extract monthly returns on all stocks from Datastream. This chapter then match rated stocks with the I/B/E/S database, leaving us with 1256 rated firms with I/B/E/S coverage over the period July 1985 through December 2002. The beginning of the sample is guided by the first time firm ratings by Standard & Poor's become available on the COMPUSTAT tapes.

Following Avramov, Chordia, Jostova and Philipov (2007), this chapter transforms the S&P rating into conventional numerical scores. Explicitly, 1 represents a rating of AAA and 22 reflects a D rating[43]. As a result, a higher numerical score is equal to a higher credit risk, or lower credit rating. The equally weighted average rating of the 1256 rated firms is 12.09 (compared to 8.83 by Avramov, Chordia, Jostova and Philipov, 2007), and the median is 12 (BB). This suggests that analysts are more interested in following high credit risk firms.

4.4 Empirical Results

4.4.1 Summary Statistics by Country

Table 4.1 reports the summary statistics for the sample. This section splits the sample into two subsamples, (i) Stocks with I/B/E/S coverage (ii) Stocks without I/B/E/S coverage. The purpose is to make sure that the sample of stocks with I/B/E/S coverage is representative. First, this section identifies an interesting feature in EPS forecasts revision. The negative revisions are higher than positive revisions in most countries. This implies

[43] The complete list of ratings is as follows. AAA=1, AA+=2, AA=3, AA−=4, A+=5, A=6, A−=7, BBB+=8, BBB=9, BBB−=10, BB+=11, BB=12, BB−=13, B+=14, B=15, B−=16, CCC+=17, CCC=18, CCC−=19, CC=20, C=21, D=22.

that initially the analysts publish optimistic estimates (evidence of this is well documented in the literature) and subsequently they revise the forecasts downwards. The findings are in line with Richardson et al. (2004) suggesting that analysts aim to maintain the flow of orders trade and provide accuracy to verify their expertise.

Table 4.1 Summary Statistics by Country

Mean size is the time series average market value of all firms in the sample and displays in millions of units of local currency. Number of stocks is the total number of firms in the sample. The forecast revision is the average of individual revisions by analysts who covered the firm in both months t-1 and t. Panel A (B) contains stocks with (without) I/B/E/S coverage. Begin dates *t* are as shown, and the ending date is December 2002.

			Panel A: Stocks with I/B/E/S coverage					Panel B: Stocks without I/B/E/S coverage	
	Begin	Total No. Stocks	No. Stocks	Mean Size	Forecast Revision			No. Stocks	Mean Size
					Negative	Zero	Positive		
Africa									
Israel	8701	588	56	2554	18%	59%	23%	532	165
South Africa	8701	1060	532	2282	32%	45%	23%	528	360
Americas (ex. U.S.)									
Argentina	9207	130	89	492	30%	45%	25%	38	160
Brazil	9207	804	296	11366	27%	47%	26%	508	1578
Canada	8501	4532	1015	391	33%	42%	25%	3517	271
Chile	9210	220	127	167966	28%	41%	31%	93	51645
Colombia	9406	145	34	356627	23%	56%	22%	111	78167
Mexico	9205	265	135	5193	33%	38%	29%	146	1266
Peru	9406	140	56	404	32%	44%	24%	73	423
Asia									
Australia	8701	1881	940	470	39%	33%	27%	941	368
China	9304	1244	296	1821	21%	62%	17%	943	3212
Hong Kong	8701	896	640	5038	34%	40%	26%	256	2755
India	9301	1185	489	8586	29%	48%	23%	696	6773
Indonesia	9005	373	238	614522	33%	40%	27%	131	573206
Japan	8701	2725	2580	178156	34%	45%	21%	101	165587
Korea	8801	1837	989	231709	30%	44%	27%	848	44202
Malaysia	8701	850	634	714	32%	40%	28%	216	562
New Zealand	8701	283	157	934	38%	35%	27%	126	325
Pakistan	9301	284	163	1694	22%	59%	18%	121	321
Philippines	8801	291	184	6417	35%	41%	24%	107	3435
Singapore	8701	576	342	598	33%	42%	26%	227	628
Taiwan	8801	744	612	17568	33%	41%	26%	130	3048
Thailand	8709	576	339	3854	33%	40%	27%	229	3967
Europe									
Austria	8701	244	112	606	30%	48%	23%	117	1276
Belgium	8701	591	144	2467	33%	41%	26%	428	5415
Denmark	8701	403	244	1835	32%	39%	29%	151	1493
Finland	8804	270	161	648	33%	41%	26%	109	636
France	8701	2005	919	1428	34%	43%	23%	1083	4141
Germany	8701	3489	922	919	32%	46%	22%	2560	2217
Greece	9211	450	262	3578	32%	44%	24%	188	2356
Ireland	8701	115	82	482	26%	50%	24%	30	421
Italy	8701	544	332	65596	32%	43%	24%	196	35832
Netherlands	8701	476	295	1323	32%	43%	25%	181	3304
Norway	8701	460	234	2201	34%	37%	28%	226	1745
Portugal	9104	216	93	1157	30%	46%	24%	123	2705
Spain	8701	240	175	5361	31%	43%	25%	59	21508
Sweden	8701	1034	376	4936	34%	40%	26%	658	5326
Switzerland	8701	739	248	2458	33%	44%	23%	490	4389
Turkey	9112	335	313	87	28%	46%	25%	22	5
UK	8701	3780	1999	2381	33%	45%	22%	1779	1200
US	8301	7122	4143	2148	26%	50%	24%	2979	1236

In addition, this section find that, for most countries, the mean size for stocks that are covered by I/B/E/S and with available returns data from Datastream is higher than stocks that are not covered by I/B/E/S. This is consistent with findings in previous literature that smaller firms are more likely to be followed by fewer analysts, as the cost of information acquisition is considerably higher for smaller firms than for the large ones.

4.4.2 Momentum Profits by Country

This section report, for each country, the profitability of momentum strategies that form portfolios based on the stocks' past six-month returns and holds the stocks for six months. For each market, stocks with performance in the bottom one-third are assigned to the loser (L) portfolio, while those in the top one-third are assigned to the winner (W) portfolio. These portfolios are equally weighted. This section uses the top and bottom one-third rather than the 10% cutoffs used by Jegadeesh and Titman (1993) because of the smaller sample sizes in most countries.

Table 4.2 displays average winner minus loser profits for each country in local currency. In Panel A, this section restricts the sample to stocks with analyst coverage only. Consistent with the overwhelming evidence documented in the literature, this section finds that momentum strategies are largely profitable on average around the world. Despite the fact that the number of stocks used in Panel A has been restricted only to those with I/B/E/S coverage, the momentum returns in this chapter are similar to those reported in Griffin et al. (2003), suggesting that this chapter is focusing on the same group of stocks. 24 of 41 countries display positive momentum profits. In addition, this chapter collects data on whether short selling is practiced from Bris, Goetzmann and Zhu (2007) - Table 1. Their data is constructed using indications from market participants, market regulators, or institutions within a country that short selling is a common practice. The results show that 18 of 23 countries display positive price momentum when short selling is a common practice. 12 of 17 countries do not experience any momentum profits when short selling is not practiced. Since Hong et al. (2000) document that momentum profits are substantially contributed by the short side, the results suggest that momentum profits could be practically implementable. However, the results do not suggest that momentum profits are necessarily linked with short-selling activity, since in most countries, short-selling is allowed only for certain stocks, in most cases, large firms. While stocks that contribute to momentum profits are smaller firms (see Hong et al, 2000). As a result, the reported results are only informative rather than conclusive.

Interestingly, this section also finds that most of the Asian countries do not experience momentum, except Australia and New Zealand stocks which exhibit significant momentum in the Asian pacific region. One question that naturally arises is why momentum profits for Asia are distinctly weaker than those around the world, especially in contrast to Europe.

Earlier studies such as Hong, Lim and Stein (2000) suggest that that momentum profits are most pronounced for small firms, growth firms and firms with low analyst coverage. If this is correct, this section should expect to see that stocks with no analyst coverage display stronger momentum and expect the sources of momentum profits to be consistent with the Hong and Stein (1999)'s gradual-information-diffusion model. Table 4.2 (Panel B) presents the momentum strategy using sample stocks that are not covered by I/B/E/S but with available returns data from Datastream. The table shows that 15 of 41 countries display momentum profits compared to 24 of 41 countries for the sample of stocks with I/B/E/S coverage in Panel A. Besides, the magnitude of the momentum profits in Panel A is much stronger than those in Panel B. The results show that the sample of stocks with I/B/E/S coverage is representative.

Table 4.2 Momentum Profits (with and without I/B/E/S coverage)

At the end of each month *t*, all stocks in each country are allocated into three portfolios based on their six month formation period from *t*-7 to *t*-2: Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30%, portfolio P2 contains the middle 40%, and portfolio P3 includes the best-performing 30%. The position is held for the following six-month period (*t* to *t*+5). This table reports the strategy's mean raw returns during the holding period. Begin dates are as shown, and the ending date is December 2002. Panel A (B) contains stocks with (without) I/B/E/S coverage. Number of stocks is the total number of firms in the sample. Countries are listed as Developed or Emerging based on the International Finance Corporation's (IFC) categorizations. *t*-statistics (in parentheses) are adjusted for autocorrelation. # Data is obtained from Bris, Goetzmann and Zhu (JoF, 2007) Table 1. *(**) Denotes significance at the 5(10) per cent level.

	Begin	Whether short selling is practiced#	Panel A: Stocks with I/B/E/S coverage					Panel B: Stocks without I/B/E/S coverage				
			No. Stocks	P3	P1	P3-P1	P3-P1 (t-stat)	No. Stocks	P3	P1	P3-P1	P3-P1 (t-stat)
Africa												
Israel	8701	No	56	-0.51	1.08	-1.59	(-2.63*)	532	-0.66	-0.04	-0.62	(-1.35)
South Africa	8701	Yes	532	1.10	-0.66	1.76	(5.51*)	528	-0.36	-1.51	1.15	(3.26*)
Americas (ex. U.S.)												
Argentina	9207	No	89	0.41	-0.07	0.48	(0.62)	41	-0.69	0.49	-1.18	(-0.98)
Brazil	9207	No	296	4.99	5.49	-0.50	(-0.33)	508	5.67	5.53	0.14	(0.10)
Canada	8501	Yes	1015	0.58	-1.08	1.66	(5.74*)	3517	-0.78	-1.79	1.01	(2.86*)
Chile	9210	No	127	1.00	0.23	0.77	(1.89**)	93	0.72	1.11	-0.39	(-1.06)
Columbia	9406	No	34	0.25	-0.91	1.16	(3.11*)	111	0.45	0.02	0.43	(1.21)
Mexico	9205	Yes	135	1.34	0.21	1.13	(3.22*)	130	1.33	0.67	0.66	(1.51)
Peru	9406	No	56	0.70	0.78	-0.08	(-0.10)	84	-1.85	-0.41	-1.44	(-0.88)
Asia												
Australia	8701	Yes	940	0.14	-1.08	1.22	(3.67*)	941	-0.71	-0.76	0.05	(0.12)
China	9304	No	296	1.04	0.74	0.30	(0.50)	948	0.47	0.21	0.26	(0.45)
Hong Kong	8701	Yes	640	-0.89	-0.58	-0.31	(-0.65)	256	-1.29	-0.80	-0.49	(-0.88)
India	9301	-	489	0.48	-0.65	1.13	(1.88**)	696	-0.47	-0.29	-0.18	(-0.32)
Indonesia	9005	No	238	-1.14	-0.54	-0.61	(-0.97)	135	-0.38	-0.51	0.13	(0.21)
Japan	8701	Yes	2580	-0.79	-0.84	0.05	(0.15)	145	-0.63	-1.06	0.43	(1.08)
Korea	8801	No	989	-1.17	-0.93	-0.24	(-0.42)	848	-1.55	-1.09	-0.46	(-0.81)
Malaysia	8701	Yes	634	0.04	0.05	-0.01	(-0.01)	216	-0.53	0.17	-0.70	(-1.03)
New Zealand	8701	No	157	0.58	-0.62	1.20	(4.22*)	126	0.47	-0.91	1.37	(3.00*)
Pakistan	9301	No	163	-0.81	-0.44	-0.36	(-0.70)	121	0.09	0.09	0.00	(0.00)
Philippines	8801	No	184	-0.40	-0.67	0.27	(0.51)	107	-0.44	0.08	-0.52	(-0.97)
Singapore	8701	Yes	342	0.05	-0.23	0.27	(0.62)	234	-0.51	-0.60	0.09	(0.17)
Taiwan	8801	No	612	-0.78	-0.93	0.14	(0.24)	132	-1.19	-1.91	0.72	(1.13)
Thailand	8709	Yes	339	-0.70	-0.32	-0.38	(-0.77)	237	-0.20	-0.36	0.16	(0.29)
Europe												
Austria	8701	Yes	112	0.32	-0.57	0.89	(2.78*)	132	0.47	-0.51	0.98	(2.88*)
Belgium	8701	Yes	144	0.76	-0.40	1.17	(4.57*)	447	0.40	0.75	1.15	(4.56*)
Denmark	8701	Yes	244	0.57	-0.36	0.93	(3.58*)	159	0.49	-0.17	0.66	(2.74*)
Finland	8804	No	161	0.25	-0.55	0.80	(1.86**)	109	0.13	-0.48	0.61	(1.59)
France	8701	Yes	919	0.39	-0.95	1.35	(4.16*)	1086	-0.12	-0.82	0.70	(2.92*)
Germany	8701	Yes	922	0.16	-1.64	1.80	(5.12*)	2567	-0.47	-1.96	1.49	(3.51*)
Greece	9211	No	262	1.36	0.51	0.84	(1.19)	188	0.89	0.46	0.43	(0.58)
Ireland	8701	Yes	82	0.47	-0.88	1.36	(4.02*)	33	-0.25	-0.84	0.59	(1.23)
Italy	8701	Yes	332	0.39	-0.34	0.73	(2.17*)	212	0.43	-0.39	0.82	(2.31*)
Netherlands	8701	Yes	295	0.51	-1.35	1.86	(5.35*)	181	0.44	-0.95	1.39	(5.28*)
Norway	8701	Yes	234	0.32	-0.54	0.86	(1.86**)	226	-0.40	-1.64	1.24	(2.70*)
Portugal	9104	Yes	93	0.15	-0.59	0.74	(2.20*)	123	-0.47	-0.32	-0.15	(-0.48)
Spain	8701	No	175	0.46	-0.40	0.86	(2.45*)	65	0.13	-0.60	0.73	(2.13*)
Sweden	8701	Yes	376	0.23	-0.98	1.21	(2.49*)	658	-0.25	-1.63	1.38	(2.70*)
Switzerland	8701	Yes	248	0.71	-0.90	1.61	(4.91*)	491	0.05	-0.68	0.73	(2.81*)
Turkey	9112	No	313	3.66	4.44	-0.78	(-0.93)	22	2.15	4.32	-2.17	(-1.92**)
UK	8701	Yes	1999	0.22	-1.64	1.86	(6.14*)	1781	-0.13	-1.82	1.69	(5.53*)
US	8301	Yes	4143	0.54	-0.83	1.37	(4.93*)	2979	-0.54	-1.35	0.81	(2.77*)

4.4.3 A test of the gradual information diffusion model of Hong and Stein (1999)

This section follows Hong, Lim and Stein (2000) to test empirically Hong and Stein's gradual information diffusion model. At the end of each month t, all stocks in each country are allocated into three portfolios based on residual analyst coverage. Portfolio (Cov)1 is an equally weighted portfolio of stocks in the lowest 30%, (Cov)2 is the middle 40%, and (Cov)3 is the highest 30%. For each of the residual analyst coverage portfolios, this section further sorts stocks into three portfolios based on returns from months t-7 to t-2. Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30%, P2 is the middle 40%, and P3 is the highest 30%. Residual analyst coverage is estimated as follows:

$$\ln(AC_{i,t}) = a_0 + a_1 \ln(Size_{i,t}) + \varepsilon_{i,t} \tag{4.5}$$

where, $AC_{i,t}$ is (1+number of analysts) of firm i at month t and $Size_{i,t}$ is the market capitalization of firm i at the beginning of month t. $\varepsilon_{i,t}$ is the residual analyst coverage.

Table 4.3 shows that momentum profits are concentrated on the highest residual analyst coverage groups (Cov3) and decrease monotonically as residual analyst coverage decreases. The findings sharply contradict Hong, Lim and Stein (2000) who found that momentum profits in the US are most severe among low residual analyst coverage firms[44]. This inconsistency leads this chapter to search for alternative behavioural based explanations.

[44] One of the possible reasons that the UK results differ from the US might be due to the difference in ownership structure. In particular, 38% of the total market value of equities are held by individuals in the US (see http://fic.wharton.upenn.edu/fic/papers/02/0216.pdf p.14) which might follow analyst opinions more than 14.9% are held by individual shareholders in the UK (see Chapter 3, p.58) .Therefore, the analyst coverage effect are much stronger in the US and in the UK.

Table 4.3 Momentum Profits and Residual Analyst Coverage

This table reports average monthly portfolios returns sorted by residual analyst coverage (Cov) and price momentum. At the end of each month *t*, all stocks in each country are allocated into three portfolios based on residual analyst coverage. Portfolio (Cov)1 is an equally weighted portfolio of stocks in the lowest 30%, (Cov)2 is the middle 40%, and (Cov)3 is the highest 30%. For each of the residual analyst coverage portfolios, this table further sort stocks into three portfolios based on returns from months t-7 to t-2. Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30%, P2 is the middle 40%, and P3 is the highest 30%. Residual analyst coverage is estimated by regressing the log (1+Analysts) on market capitalisation and log (Size). #(##) represents countries with momentum in Table 4.2 at 5(10)% significant level. t-statistics in parentheses are adjusted for autocorrelation. *(**) Denotes significance at the 5(10) per cent level.

	Cov3 (High)				Cov2				Cov1 (Low)			
	P3	P1	P3-P1	P3-P1 (t-stat)	P3	P1	P3-P1	P3-P1 (t-stat)	P3	P1	P3-P1	P3-P1 (t-stat)
Africa												
Israel	1.04	0.58	0.46	(0.74)	0.85	-0.05	0.90	(1.75**)	0.18	-0.83	1.01	(1.61)
South Africa #	0.54	-0.84	1.38	(3.75*)	0.67	-0.53	1.20	(3.42*)	0.69	-0.45	1.14	(3.39*)
Americas (ex. U.S.)												
Argentina	-0.90	-1.94	1.04	(1.51)	-0.04	-1.26	1.23	(2.07*)	-0.35	-1.18	0.84	(1.19)
Brazil	-1.20	-1.41	0.21	(0.30)	-0.35	-0.88	0.53	(0.71)	-0.50	-0.81	0.30	(0.37)
Canada #	0.14	-2.00	2.14	(8.28*)	0.41	-1.31	1.72	(6.78*)	0.70	-0.84	1.54	(5.76*)
Chile ##	0.08	-1.08	1.16	(2.42*)	0.48	-0.23	0.71	(1.60)	0.52	-0.14	0.66	(1.57)
Columbia #	-1.11	-2.87	1.76	(1.93**)	-0.59	-2.24	1.65	(2.52*)	-0.31	-0.98	0.67	(1.12)
Mexico #	0.31	0.56	-0.25	(-0.52)	0.66	-0.06	0.72	(1.41)	-0.77	-0.88	0.11	(0.16)
Peru	-0.91	-2.00	1.09	(1.37)	-1.74	-1.68	-0.06	(-0.07)	-0.52	-0.23	-0.28	(-0.37)
Asia												
Australia #	0.37	-2.53	2.90	(8.91*)	0.49	-1.16	1.65	(5.98*)	0.99	-0.84	1.83	(6.02*)
China	-0.60	-1.29	0.69	(0.89)	0.47	0.26	0.21	(0.27)	1.14	0.40	0.74	(0.83)
Hong Kong	-0.29	-1.38	1.09	(2.30*)	0.16	-0.79	0.95	(2.14*)	-0.07	-0.82	0.75	(1.62)
India ##	-0.99	-2.54	1.54	(2.39*)	0.00	-1.79	1.79	(3.08*)	0.85	-0.63	1.48	(2.16*)
Indonesia	-1.75	-1.90	0.15	(0.19)	-0.92	-1.15	0.23	(0.34)	-0.71	-0.97	0.26	(0.35)
Japan	-0.92	-1.02	0.10	(0.32)	-0.78	-0.79	0.01	(0.03)	-0.38	-0.52	0.14	(0.41)
Korea	-0.28	-0.47	0.19	(0.33)	-0.77	-0.80	0.03	(0.06)	-1.14	-1.00	-0.14	(-0.26)
Malaysia	0.29	0.01	0.28	(0.54)	0.32	-0.12	0.44	(0.89)	0.29	0.00	0.29	(0.53)
New Zealand #	0.76	-1.76	2.52	(6.19*)	0.94	-0.81	1.75	(5.72*)	0.91	0.59	0.32	(0.81)
Pakistan	-0.57	-0.66	0.09	(0.11)	-0.94	-1.28	0.34	(0.45)	-1.39	-0.09	-1.30	(-1.65)
Philippines	-1.39	-1.32	-0.07	(-0.08)	-0.35	-2.23	1.88	(2.54*)	-1.90	-1.66	-0.24	(-0.36)
Singapore	-0.05	-0.56	0.51	(1.03)	0.06	-0.47	0.53	(1.28)	-0.04	-0.20	0.16	(0.35)
Taiwan	-0.61	-0.64	0.03	(0.05)	-0.90	-0.53	-0.37	(-0.61)	-0.64	-0.51	-0.13	(-0.21)
Thailand	-1.18	-1.46	0.28	(0.44)	-0.58	-1.21	0.63	(1.18)	-0.68	-1.08	0.40	(0.68)
Europe												
Austria #	0.32	-0.63	0.95	(2.09*)	0.13	-0.76	0.89	(2.19*)	0.08	-0.44	0.52	(1.38)
Belgium #	0.80	-0.12	0.92	(3.25*)	0.64	-0.44	1.08	(3.49*)	0.73	-0.25	0.98	(3.05*)
Denmark #	0.42	-1.01	1.43	(4.39*)	0.85	-0.49	1.34	(4.92*)	0.62	-0.45	1.07	(3.56*)
Finland ##	0.85	0.53	0.32	(0.59)	0.67	-0.18	0.85	(1.65)	-0.65	-1.01	0.36	(0.65)
France #	0.43	-1.48	1.91	(4.41*)	0.67	-0.75	1.42	(4.00*)	0.53	-0.39	0.92	(2.74*)
Germany #	-0.72	-2.08	1.36	(2.85*)	-0.43	-1.58	1.15	(2.70*)	-0.05	-1.05	1.00	(2.92*)
Greece	0.88	0.53	0.35	(1.65)	1.26	0.24	1.02	(1.13)	1.08	0.18	0.90	(1.01)
Ireland #	0.63	-1.40	2.03	(4.15*)	0.92	-0.63	1.55	(3.99*)	-0.09	-0.26	0.17	(0.43)
Italy #	0.13	-0.71	0.84	(2.18*)	0.38	-0.64	1.02	(2.90*)	0.22	-0.36	0.58	(1.59)
Netherlands #	0.87	-1.50	2.37	(5.24*)	0.78	-0.72	1.50	(4.31*)	0.37	-0.55	0.92	(2.72*)
Norway ##	-0.44	-0.64	0.20	(0.35)	0.49	-0.55	1.04	(2.21*)	0.59	-0.77	1.36	(2.70*)
Portugal #	0.38	-0.74	1.12	(1.85**)	0.89	0.16	0.73	(1.57)	0.21	0.03	0.18	(0.38)
Spain #	-0.11	-0.96	0.85	(2.01*)	0.57	-0.15	0.72	(2.05*)	0.67	0.32	0.35	(0.93)
Sweden #	0.71	-1.11	1.82	(3.35*)	0.13	-1.22	1.35	(2.83*)	0.28	-0.78	1.06	(2.35*)
Switzerland #	0.36	-1.03	1.39	(3.82*)	0.36	-0.77	1.13	(3.21*)	0.48	-0.60	1.08	(3.30*)
Turkey	3.37	4.61	-1.24	(-1.30)	3.25	4.79	-1.54	(-1.59)	3.23	4.79	-1.56	(-1.54)
UK #	0.42	-1.83	2.25	(6.76*)	0.35	-1.01	1.36	(4.99*)	0.28	-1.19	1.47	(4.65*)
US #	0.40	-0.32	0.72	(3.85*)	0.55	-0.85	1.30	(5.86*)	0.45	-1.10	1.55	(7.15*)

4.4.4 *Dispersion in analysts' forecast and momentum profits*

Using dispersion of analysts' earnings forecasts to proxy for divergence of opinion, Diether, Malloy and Scherbina (2002) find that stocks with higher dispersion in analysts' earnings forecasts tend to have lower future returns. On the other hand, Zhang (2006) employ dispersion of analysts' forecasts to proxy for information uncertainty, and find that higher dispersion in analysts' forecast stocks experience higher momentum profits that are mainly contributed from the loser stocks i.e. lower future returns. This section examines the link between dispersion in analyst forecast and momentum profits for the global data.

Table 4.4 presents the payoff of momentum portfolios sorted on dispersion in analysts' earnings forecast (Disp). At the end of each month *t*, all stocks in each country are allocated into three portfolios based on forecast dispersion. Portfolio Disp1 is an equally weighted portfolio of stocks in the lowest 30%, Disp2 is the middle 40%, and Disp3 is the highest 30%. For each of the forecast dispersion portfolios, this section further sorts stocks into three portfolios based on returns from months t-7 to t-2. Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30%, P2 is the middle 40%, and P3 is the highest 30%.

Table 4.4 Portfolios Returns by Price Momentum and Dispersion of Analysts Forecast (Disp)

This table reports average monthly portfolio returns sorts by dispersion of analysts' forecast (Disp) and price momentum. At the end of each month *t*, all stocks in each country are allocated into three portfolios based on forecast dispersion. Portfolio Disp1 is an equally weighted portfolio of stocks in the lowest 30%, Disp2 is the middle 40%, and Disp3 is the highest 30%. For each of the forecast dispersion portfolios, this table further sorts stocks into three portfolios based on returns from months t-7 to t-2. Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30%, P2 is the middle 40%, and P3 is the highest 30%. Disp is the standard deviation of analyst forecasts in month t scaled by the prior year end stock price. #(##) represents countries with momentum in Table 4.2 at 5(10)% significant level. t-statistics in parentheses are adjusted for autocorrelation. *(**) Denotes significance at the 5(10) per cent level.

	Disp 3 (High)				Disp 2				Disp 1 (Low)			
	P3	P1	P3-P1	P3-P1 (t-stat)	P3	P1	P3-P1	P3-P1 (t-stat)	P3	P1	P3-P1	P3-P1 (t-stat)
Africa												
Israel	-0.13	0.41	-0.54	(-0.63)	1.47	0.76	0.71	(1.48)	0.99	0.68	0.31	(0.61)
South Africa #	0.74	-0.77	1.51	(3.68*)	0.83	-0.28	1.11	(3.02*)	0.81	0.37	0.44	(1.21)
Americas (ex. U.S.)												
Argentina	-2.96	-3.57	0.61	(0.73)	-0.46	-0.55	0.09	(0.14)	0.07	-0.23	0.30	(0.43)
Brazil	0.81	1.58	-0.77	(-0.73)	1.01	1.52	-0.51	(-0.68)	0.57	0.78	-0.21	(-0.18)
Canada #	-0.16	-2.30	2.14	(7.01*)	0.43	-0.69	1.12	(4.34*)	1.09	-0.09	1.18	(4.15*)
Chile ##	0.23	0.41	-0.18	(-0.36)	0.35	-0.07	0.42	(0.98)	0.09	0.17	-0.08	(-0.19)
Columbia #	1.14	-1.55	2.69	(2.93*)	-0.85	-1.39	0.54	(0.73)	0.32	0.00	0.32	(0.37)
Mexico #	-0.96	-2.17	1.21	(2.01*)	0.25	-0.60	0.85	(1.49)	0.47	0.11	0.36	(0.74)
Peru	0.16	-1.89	2.05	(1.76**)	-1.61	-1.79	0.18	(0.25)	-2.10	0.23	-2.33	(-2.66*)
Asia												
Australia #	0.40	-1.52	1.92	(6.66*)	0.51	-0.97	1.48	(5.60*)	0.89	-0.13	1.02	(4.85*)
China	-0.83	-0.69	-0.14	(-0.16)	0.09	0.35	-0.26	(-0.29)	0.31	0.14	0.17	(0.18)
Hong Kong	-0.03	-0.82	0.79	(1.80**)	-0.11	-0.53	0.42	(0.91)	0.40	-0.11	0.51	(1.12)
India ##	-0.29	-2.30	2.01	(2.48*)	0.34	-1.05	1.39	(2.68*)	1.40	-0.03	1.43	(2.29*)
Indonesia	-1.59	-1.70	0.11	(0.17)	-1.48	-0.69	-0.79	(-0.99)	-1.16	0.05	1.21	(-1.47)
Japan	-0.47	-1.01	0.54	(1.47)	-0.55	-0.54	-0.01	(-0.04)	-0.71	-0.65	-0.06	(-0.17)
Korea	-0.91	-0.48	-0.43	(-0.76)	-0.88	0.09	-0.97	(-1.91**)	-0.36	0.01	-0.37	(-0.73)
Malaysia	0.51	-0.09	0.60	(1.04)	0.49	0.31	0.18	(0.36)	0.56	0.72	-0.16	(-0.29)
New Zealand #	-0.18	-2.94	2.76	(5.35*)	0.35	-1.20	1.55	(4.22*)	1.12	-0.17	1.29	(3.33*)
Pakistan	-1.13	-1.53	0.40	(0.42)	-1.12	-1.33	0.21	(0.25)	-0.62	0.11	-0.73	(-0.89)
Philippines	-0.86	-2.25	1.39	(2.24*)	-0.87	-1.54	0.67	(1.04)	-0.36	-1.26	0.90	(1.44)
Singapore	0.22	-0.57	0.79	(1.78**)	0.39	-0.15	0.54	(1.20)	0.39	0.11	0.28	(0.64)
Taiwan	-1.64	-1.38	-0.26	(-0.43)	-0.27	0.10	-0.37	(-0.75)	0.73	0.52	0.21	(0.42)
Thailand	-1.32	-1.04	-0.28	(-0.43)	-1.46	-1.41	-0.05	(-0.09)	-0.58	-0.92	0.34	(0.56)
Europe												
Austria #	0.15	-1.20	1.35	(2.75*)	0.21	-0.33	0.54	(1.49)	0.59	0.44	0.15	(0.36)
Belgium #	0.26	0.19	0.07	(0.25)	0.30	-0.37	0.67	(2.52*)	1.31	0.04	1.27	(4.46*)
Denmark #	0.08	-0.92	1.00	(2.79*)	0.35	-0.10	0.45	(1.58)	1.02	0.41	0.61	(1.83**)
Finland ##	0.44	-0.29	0.73	(1.08)	0.85	0.47	0.38	(0.73)	1.17	0.93	0.24	(0.38)
France #	0.04	-0.83	0.87	(2.50*)	0.53	0.05	0.48	(1.55)	1.46	0.56	0.90	(2.33*)
Germany #	-2.92	-5.82	2.90	(3.46*)	-1.50	-4.29	2.79	(3.27*)	-1.54	-3.19	1.65	(2.20*)
Greece	1.23	0.28	0.95	(1.49)	1.22	1.05	0.17	(0.22)	1.82	0.95	0.87	(0.98)
Ireland #	-0.24	-2.22	1.98	(3.75*)	0.96	0.03	0.93	(2.78*)	0.62	0.42	0.20	(0.43)
Italy #	-0.44	-1.10	0.66	(1.52)	0.35	0.11	0.24	(0.69)	1.15	0.79	0.36	(0.89)
Netherlands #	-0.05	-1.00	0.95	(2.21*)	0.81	0.09	0.72	(2.46*)	1.23	0.54	0.69	(2.24*)
Norway ##	-0.08	-0.17	0.09	(0.15)	0.42	0.44	-0.02	(-0.04)	1.60	0.33	1.27	(2.76*)
Portugal #	-0.15	-1.12	0.97	(1.77**)	0.52	0.39	0.13	(0.30)	1.59	0.85	0.74	(1.55)
Spain #	-0.06	-1.46	1.40	(2.88*)	0.43	-0.08	0.51	(1.35)	0.71	0.63	0.08	(0.25)
Sweden #	-1.37	-1.30	-0.07	(-0.11)	0.42	0.44	-0.02	(-0.05)	1.74	1.21	0.53	(1.35)
Switzerland #	-0.29	-1.08	0.79	(1.87**)	0.71	0.11	0.60	(1.99*)	1.31	0.52	0.79	(2.68*)
Turkey	2.73	4.36	-1.63	(-1.68**)	3.19	4.58	-1.39	(-1.44)	3.85	4.78	-0.93	(-0.97)
UK #	-0.17	-2.47	2.30	(6.19*)	0.32	-1.06	1.38	(4.76*)	0.79	-0.67	1.46	(5.19*)
US #	-0.54	-1.95	1.41	(4.16*)	0.34	-0.34	0.68	(2.77*)	1.45	0.67	0.78	(3.83*)

Table 4.4 shows that momentum profits are concentrated on the highest dispersion in analysts' forecast groups (Disp 3) and decrease monotonically as dispersion in analysts' forecasts decrease. 17 of 24 countries that have experienced momentum profits in Table 4.2 display this pattern. Remarkably, countries such as Peru, Hong Kong, Philippines and Singapore which display no momentum profits in Table 4.2 have also documented the above pattern. The results are contributed substantially by loser stocks that earn lower future returns. As a result, the findings are consistent with Zhang (2006) who used dispersion in analysts' forecast to proxy for uncertainty rather than divergence in opinion as suggested by Diether, Malloy and Scherbina (2002).

4.4.5 *Uncertainty and momentum profits*

One major problem of using dispersion in analysts' forecasts to proxy for uncertainty is that forecast dispersion is contaminated by the effect of investors' disagreement (see Baron, Kim, Lim and Stevens (1998)). As a result, this section examines the link between BKLS measure of uncertainty and momentum profits to the global data.

Table 4.5 reports average monthly portfolio returns sorts by uncertainty (V) and price momentum. At the end of each month *t*, all stocks in each country are allocated into three portfolios based on uncertainty. Portfolio V1 is an equally weighted portfolio of stocks in the lowest 30%, V2 is the middle 40%, and V3 is the highest 30%. For each of the uncertainty portfolios, this section further sorts stocks into three portfolios based on returns from months t-7 to t-2. Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30%, P2 is the middle 40%, and P3 is the highest 30%.

Table 4.5 presents a strong link between uncertainty and momentum profits. Momentum profits are concentrated on the highest uncertainty groups (V3) and decrease monotonically as uncertainty decreases. 15 of 24 countries that have experienced momentum profits in Table 4.2 display this pattern. Interestingly, Peru and Greece which display no momentum profits have also documented the above pattern. The findings are consistent with hypothesis 1 suggesting a strong link between momentum profits and uncertainty measured by dispersion in analysts' forecast and BKLS's uncertainty.

Table 4.5 Portfolios Returns by Price Momentum and Uncertainty (V)

This table reports average monthly portfolio returns sorted by uncertainty (V) and price momentum. At the end of each month *t*, all stocks in each country are allocated into three portfolios based on uncertainty. Portfolio V1 is an equally weighted portfolio of stocks in the lowest 30%, V2 is the middle 40%, and V3 is the highest 30%. For each of the uncertainty portfolio, this table further sorts stocks into three portfolios based on returns from months t-7 to t-2. Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30%, P2 is the middle 40%, and P3 is the highest 30%. V, the uncertainty measure, is computed as in BKLS (1998). #(##) represents countries with momentum in Table 4.2 at 5(10)% significant level. t-statistics in parentheses are adjusted for autocorrelation. *(**) Denotes significance at the 5(10) per cent level.

	V3 (High)				V2				V1 (Low)			
	P3	P1	P3-P1	P3-P1 (t-stat)	P3	P1	P3-P1	P3-P1 (t-stat)	P3	P1	P3-P1	P3-P1 (t-stat)
Africa												
Israel	0.12	-0.90	1.02	(1.22)	1.31	0.35	0.96	(1.94**)	0.72	0.06	0.66	(1.14)
South Africa #	0.14	-1.62	1.76	(3.89*)	0.62	0.33	0.29	(0.81)	1.17	0.57	0.60	(1.96**)
Americas (ex. U.S.)												
Argentina	-3.19	-3.47	0.28	(0.35)	-0.90	-0.93	0.03	(0.05)	0.47	-0.28	0.75	(1.17)
Brazil	0.82	1.69	-0.87	(-0.86)	0.84	1.03	-0.19	(-0.23)	0.70	1.08	-0.38	(-0.35)
Canada #	-0.96	-2.51	1.55	(4.97*)	0.93	-0.44	1.37	(5.11*)	1.42	0.53	0.89	(3.69*)
Chile ##	-0.37	-0.33	-0.04	(-0.08)	0.69	0.26	0.43	(0.99)	0.50	0.79	-0.29	(-0.76)
Columbia #	1.17	-1.76	2.93	(3.48*)	-0.49	-0.50	0.01	(0.01)	0.01	0.49	-0.48	(-0.61)
Mexico #	-1.45	-2.43	0.98	(1.70**)	-0.02	-0.78	0.76	(1.25)	0.36	-0.02	0.38	(0.74)
Peru	-0.57	-4.33	3.76	(2.57*)	-1.61	-0.83	-0.78	(-0.99)	-1.61	0.89	-2.50	(-2.84*)
Asia												
Australia #	-0.22	-2.10	1.88	(5.75*)	0.78	-0.32	1.10	(4.46*)	1.11	0.48	0.63	(3.51*)
China	-1.02	-1.00	-0.02	(-0.01)	0.06	0.59	-0.53	(0.60)	0.50	0.83	-0.33	(-0.36)
Hong Kong	-1.36	-1.41	0.05	(0.09)	0.04	-0.10	0.14	(0.30)	0.97	0.68	0.29	(0.74)
India ##	-0.68	-2.45	1.77	(2.25*)	0.48	-0.82	1.30	(2.11*)	1.03	0.17	0.86	(1.52)
Indonesia	-2.28	-1.88	-0.40	(-0.55)	-1.28	-0.70	-0.58	(-0.74)	-0.76	-0.08	-0.68	(-0.96)
Japan	-1.16	-1.28	0.12	(0.30)	-0.41	-0.44	0.03	(0.07)	-0.27	-0.28	0.01	(0.01)
Korea	-1.76	-0.83	-0.93	(-1.50)	-0.56	0.07	-0.63	(-1.26)	-0.03	0.38	-0.41	(-0.90)
Malaysia	0.50	-0.22	0.72	(1.24)	0.66	0.57	0.09	(0.16)	0.45	0.71	-0.26	(-0.54)
New Zealand #	-1.07	-2.65	1.58	(3.22*)	0.94	-0.05	0.99	(2.99*)	1.24	0.51	0.73	(2.38*)
Pakistan	-2.74	-1.63	-1.11	(-1.13)	-0.69	-1.00	0.31	(0.34)	-1.22	-0.53	-0.69	(-0.79)
Philippines	-1.89	-3.21	1.32	(1.70**)	-0.40	-0.61	0.21	(0.32)	0.50	-0.87	1.37	(2.11*)
Singapore	-0.34	-0.55	0.21	(0.43)	0.35	-0.16	0.51	(1.14)	0.66	0.47	0.19	(0.44)
Taiwan	-1.57	-1.53	-0.04	(-0.07)	0.00	0.08	-0.08	(-0.16)	0.46	0.44	0.02	(0.03)
Thailand	-2.52	-1.24	-1.28	(-1.74**)	-1.22	-0.97	-0.25	(-0.45)	-0.18	-0.60	0.42	(0.79)
Europe												
Austria #	-0.11	-0.99	0.88	(1.98*)	0.50	-0.23	0.73	(1.96**)	0.47	0.77	-0.30	(-0.83)
Belgium #	-0.26	-0.33	0.07	(0.19)	0.54	0.07	0.61	(2.46*)	1.37	0.28	1.09	(4.37*)
Denmark #	-0.28	-1.58	1.30	(3.18*)	0.37	0.29	0.08	(0.28)	1.41	0.62	0.79	(2.97*)
Finland ##	-0.72	-0.20	-0.52	(-0.76)	0.94	0.07	0.87	(1.41)	1.32	0.87	0.45	(0.93)
France #	-0.66	-1.62	0.96	(2.34*)	0.73	-0.15	0.88	(2.33*)	1.55	0.91	0.64	(2.03*)
Germany #	-1.13	-2.27	1.14	(2.30*)	0.17	-0.57	0.74	(1.95**)	0.73	-0.09	0.82	(2.66*)
Greece	1.21	-0.20	1.41	(1.86**)	1.14	0.82	0.32	(0.43)	1.71	1.40	0.31	(0.40)
Ireland #	-0.49	-2.46	1.97	(3.57*)	0.82	0.66	0.16	(0.44)	1.25	0.97	0.28	(0.77)
Italy #	-0.43	-1.07	0.64	(1.48)	0.44	-0.04	0.48	(1.34)	1.01	0.77	0.24	(0.65)
Netherlands #	-0.68	-1.03	0.35	(0.84)	1.06	0.03	1.03	(3.02*)	1.43	1.08	0.35	(1.45)
Norway ##	-1.09	-0.29	-0.80	(-1.25)	0.32	0.26	0.06	(0.14)	1.97	0.92	1.05	(2.68*)
Portugal #	-0.18	-0.97	0.79	(1.36)	1.07	-0.16	1.23	(2.60*)	1.40	1.12	0.28	(0.65)
Spain #	-0.62	-1.60	0.98	(1.96**)	0.54	0.34	0.20	(0.54)	1.03	0.72	0.31	(0.99)
Sweden #	-1.31	-0.97	-0.34	(-0.58)	0.21	-0.02	0.23	(0.51)	2.19	1.31	0.88	(2.51*)
Switzerland #	-0.07	-0.89	0.82	(2.14*)	0.60	-0.23	0.83	(2.48*)	1.40	0.43	0.97	(3.33*)
Turkey	2.58	3.82	-1.24	(-1.23)	3.12	4.88	-1.76	(-1.80**)	3.92	4.95	-1.03	(-1.06)
UK #	-0.15	-2.38	2.23	(5.63*)	0.62	-0.64	1.26	(4.92*)	0.89	-0.22	1.11	(4.58*)
US #	-0.64	-3.21	2.57	(6.82*)	0.40	-1.21	1.61	(6.65*)	1.25	0.06	1.19	(6.31*)

4.4.6 *Diversity of analysts' forecast and momentum profits*

Results in the previous section demonstrate that the level of analysts' forecasts mainly reflects uncertainty. This section examines the relation between diversity of analyst forecast (1-ρ) that proxy for disagreement and momentum profits. Since winner stocks continue to go up and loser stocks continue to go down a high level of consensus is required. This chapter hypothesises that expected momentum profits are high when diversity of analysts' forecasts are low.

Table 4.6 reports average monthly portfolio returns sorted by diversity in analyst forecast (1-ρ) and price momentum. At the end of each month *t*, all stocks in each country are allocated into three portfolios based on diversity of analyst forecast. Portfolio (1-ρ)1 is an equally weighted portfolio of stocks in the lowest 30%, (1-ρ)2 is the middle 40%, and (1-ρ)3 is the highest 30%. For each of the diversity in analyst forecast portfolios, this section further sorts stocks into three portfolios based on returns from months t-7 to t-2. Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30%, P2 is the middle 40%, and P3 is the highest 30%.

Table 4.6 establishes a strong link between diversity in analysts' forecast and momentum profits. In particular, this section finds that 16 of 24 countries experience the highest momentum profits among the lowest diversity in analyst forecast groups and decrease monotonically when diversity in analysts' forecast increases[45]. Since the success of momentum strategies require a high level of agreement among investors in order to push prices into the same direction, the findings show that momentum profits are concentrated in low diversity in analysts' forecast stocks (i.e. low disagreement). As a result, the findings in this section provide empirical evidence to support the view that diversity in analysts' forecast is a better proxy for disagreement.

[45] One of the possible reasons that the UK results differ from the US might be due to the difference in ownership structure. (see footnote 44, p106)

Table 4.6 Momentum Profits and Diversity of Analyst Forecast (1- ρ)

This table reports average monthly portfolio returns sorted by diversity in analyst forecast (1-ρ) and price momentum. At the end of each month *t*, all stocks in each country are allocated into three portfolios based on diversity of analyst forecast. Portfolio (1-ρ)1 is an equally weighted portfolio of stocks in the lowest 30%, (1-ρ)2 is the middle 40%, and (1-ρ)3 is the highest 30%. For each of the diversity in analyst forecast portfolio, this table further sorts stocks into three portfolios based on returns from months t-7 to t-2. Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30%, P2 is the middle 40%, and P3 is the highest 30%. (1-ρ), the diversity of opinion measure, is computed as in BKLS (1998). #(##) represents countries with momentum in Table 4.2 at 5(10)% significant level. t-statistics in parentheses are adjusted for autocorrelation. *(**) Denotes significance at the 5(10) per cent level.

	(1-ρ) 3 High				(1-ρ) 2				(1-ρ) 1 Low			
	P3	P1	P3-P1	P3-P1 (t-stat)	P3	P1	P3-P1	P3-P1 (t-stat)	P3	P1	P3-P1	P3-P1 (t-stat)
Africa												
Israel	1.33	1.43	-0.10	(-0.18)	0.77	0.47	0.30	(0.51)	0.51	0.15	0.36	(0.51)
South Africa #	0.70	0.36	0.34	(0.92)	0.84	-0.34	1.18	(3.41*)	0.48	-0.84	1.32	(3.21*)
Americas (ex. U.S.)												
Argentina	-0.56	-0.92	0.36	(0.51)	-1.26	-1.71	0.45	(0.60)	-1.66	-2.36	0.70	(0.99)
Brazil	0.76	1.63	-0.87	(-0.86)	0.86	1.41	-0.55	(-0.64)	0.14	1.03	-0.89	(-0.84)
Canada #	1.00	-0.48	1.48	(5.97*)	0.72	-0.98	1.70	(6.45*)	0.25	-1.67	1.92	(6.60*)
Chile ##	0.95	0.54	0.41	(1.04)	-0.11	0.27	-0.38	(-0.84)	-0.07	-0.40	0.33	(0.69)
Columbia #	1.26	-0.52	1.78	(2.09*)	-0.37	-0.52	0.15	(0.23)	0.57	-0.97	1.54	(2.11*)
Mexico #	0.32	-0.11	0.43	(0.73)	0.06	-0.62	0.68	(1.28)	0.31	-1.34	1.65	(2.72*)
Peru	-1.63	-0.37	-1.26	(-1.20)	-0.29	-1.22	0.93	(0.92)	-2.60	-2.77	0.17	(0.19)
Asia												
Australia #	0.86	-0.27	1.13	(4.79*)	0.64	-0.68	1.32	(5.49*)	0.19	-1.46	1.65	(5.97*)
China	0.42	1.22	-0.80	(-0.92)	0.01	0.20	-0.19	(-0.21)	-0.39	-0.95	0.56	(0.59)
Hong Kong	0.41	0.36	0.05	(0.12)	0.30	-0.27	0.57	(1.32)	-0.74	-1.21	0.47	(0.89)
India ##	0.56	-0.55	1.11	(1.60)	0.53	-1.69	2.22	(3.64*)	0.08	-1.60	1.68	(2.34*)
Indonesia	-0.79	-0.39	-0.40	(-0.54)	-1.38	-0.89	-0.49	(-0.70)	-2.14	-1.59	-0.55	(-0.64)
Japan	-0.43	-0.52	0.09	(0.27)	-0.54	-0.61	0.07	(0.21)	-0.92	-1.05	0.13	(0.37)
Korea	-0.44	0.18	-0.62	(-1.30)	-0.69	-0.04	-0.65	(-1.24)	-1.00	-0.51	-0.49	(-0.83)
Malaysia	0.33	0.43	-0.10	(-0.20)	0.49	0.25	0.24	(0.44)	0.63	0.27	0.36	(0.64)
New Zealand #	0.73	-0.48	1.21	(3.28*)	0.61	-0.78	1.39	(4.20)	0.27	-1.41	1.68	(4.55*)
Pakistan	-1.88	-1.29	-0.59	(-0.56)	-0.39	-1.65	1.26	(1.43)	-1.36	0.34	-1.70	(-1.83**)
Philippines	0.64	-0.60	1.24	(1.87**)	-1.02	-1.36	0.34	(0.54)	-1.09	-2.39	1.30	(1.71**)
Singapore	0.67	0.13	0.54	(1.23)	0.34	-0.19	0.53	(1.20)	0.04	-0.32	0.36	(0.76)
Taiwan	0.04	0.18	-0.14	(-0.29)	-0.18	-0.32	0.14	(0.27)	-0.53	-1.07	0.54	(0.88)
Thailand	-0.50	-1.19	0.69	(1.21)	-1.32	-1.43	0.11	(0.18)	-1.81	-0.82	-0.99	(-1.42)
Europe												
Austria #	0.27	-0.09	0.36	(0.95)	0.52	-0.12	0.64	(1.57)	0.48	-0.64	1.12	(2.56*)
Belgium #	0.66	0.26	0.40	(1.60)	0.68	-0.01	0.69	(2.06*)	0.40	-0.42	0.82	(2.32*)
Denmark #	0.32	-0.15	0.47	(1.75**)	0.77	0.18	0.59	(1.92**)	0.13	-0.98	1.11	(3.01*)
Finland ##	1.04	0.07	0.97	(1.59)	0.62	0.42	0.20	(0.40)	0.72	0.42	0.30	(0.42)
France #	0.81	0.39	0.42	(1.30)	0.83	-0.21	1.04	(2.99*)	0.35	-1.66	2.01	(4.46*)
Germany #	0.43	-0.65	1.08	(3.20*)	0.20	-1.05	1.25	(3.37*)	-0.32	-1.89	1.57	(3.33*)
Greece	1.19	0.88	0.31	(0.41)	1.17	0.93	0.24	(0.32)	1.47	0.79	0.68	(0.83)
Ireland #	0.42	-0.28	0.70	(1.71**)	1.05	-0.18	1.23	(2.93*)	0.38	-1.43	1.81	(3.42*)
Italy #	0.52	0.13	0.39	(0.96)	0.48	-0.02	0.50	(1.30)	0.08	-0.56	0.64	(1.54)
Netherlands #	0.98	-0.42	1.40	(3.92*)	0.91	0.35	0.56	(1.70**)	0.38	-0.41	0.79	(2.40*)
Norway ##	0.92	0.52	0.40	(0.79)	0.91	0.35	0.56	(1.22)	-0.11	-0.42	0.31	(0.54)
Portugal #	0.76	0.01	0.75	(1.56)	0.86	-0.05	0.91	(2.06*)	0.61	-0.77	1.38	(2.42*)
Spain #	0.85	0.36	0.49	(1.33)	0.68	-0.04	0.72	(2.04*)	-0.25	-1.25	1.00	(2.22*)
Sweden #	1.23	0.34	0.89	(2.19*)	0.67	-0.25	0.92	(2.33*)	0.06	-1.01	1.07	(1.89**)
Switzerland #	0.81	0.18	0.63	(2.05*)	0.73	-0.14	0.87	(2.87*)	0.55	-0.77	1.32	(3.22*)
Turkey	3.08	4.83	-1.75	(-1.83**)	3.22	4.35	-1.13	(-1.16)	3.34	4.70	-1.36	(-1.33)
UK #	0.73	-0.56	1.29	(3.31*)	0.52	-0.96	1.48	(4.97*)	0.54	-1.61	2.15	(5.85*)
US #	-0.18	-1.63	1.45	(5.02*)	0.30	-0.60	0.90	(3.49*)	1.27	0.13	1.14	(4.45*)

4.4.7 *Uncertainty, analyst bias and momentum profits*

This section examines the link between uncertainty, analyst bias and momentum profits. Zhang (2006) suggests that momentum profits are high when uncertainty is high. In addition, greater information uncertainty produces higher future returns following good news and lower future returns following bad news. The author traces the sources of momentum profits to the slow absorption of ambiguous information into stock price. This section incorporates analyst bias to examine how information incorporates into prices slowly under high uncertainty.

This section performs a three dimension analysis by first sorting stocks at the end of each month t into three portfolios based on uncertainty (V). This section then independently sorts stocks into three portfolios based on analyst bias (AB). All stocks within each element of the matrix (V x AB) are then allocated into three portfolios based on their prior six-month returns. P1 includes the worst performing 30%, P2 includes the middle 40% (unreported), and P3 includes the best performing 30%[46].

Table 4.7 reports the portfolio's mean raw returns during the six months holding period (Ret 7-12) and the next six months after the holding period (Ret 13-18)[47]. Momentum profits are most concentrated among the high uncertainty and high analyst bias group, decreasing monotonically with uncertainty and analysts' bias decrease. In addition, loser stocks are the dominant source of return continuation and the profitability of momentum strategies. 23 of 41 countries display such a pattern. Moreover, the results show that, in most countries, loser stocks continue to perform poorly during the next six months after the holding period (Ret 13-18), suggesting that loser stocks continue to lag behind, this is consistent with Jegadeesh and Titman's (1993) findings that the serial correlation of returns can be found up to the 12 month horizon.

[46] The number of firms that is left in to each ultimate portfolio as a result of sorting procedure is ranging from 10 to 236 firms.
[47] Table 4.7 drops Israel, Brazil, Columbia and Peru for insufficient data.

Table 4.7 Momentum Profits, Uncertainty and Analyst Bias

This table reports average monthly portfolio returns sorted by uncertainty (V) and analyst bias (AB). At the end of each month *t*, all stocks in each country are allocated into three portfolios based on uncertainty. Portfolio V1 (V3) is an equally weighted portfolio of stocks in the lowest (highest) 30%, V2 is the middle 40%. For each of the uncertainty portfolio, this table further sorts stocks into three portfolios based on analyst bias. Portfolio AB1 (AB3) is an equally weighted portfolio of stocks in the lowest (highest) 30%. Portfolio P1 (P3) is an equally weighted portfolio of stocks in the worst (best) performing 30%, P2 (in Appendix 6) is the middle 40%. The momentum strategy (P3-P1) is calculated in the manner described in Table 4.2., the average monthly momentum profits over the six months holding period (Ret 7-12) and the next six months after the holding period (Ret 13-18) are reported, T-stat of (P3-P1) is presented in Appendix 6. #(##) represents countries with momentum in Table 4.2 at 5(10)% significant level. *(**) Denotes significance at the 5(10) per cent level.

		V3 (High)						V2						V1 (Low)					
		AB3			AB1			AB3			AB1			AB3			AB1		
Africa		P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1
South Africa #	Ret 7-12	-0.41	-2.58	2.17*	0.46	0.22	0.68	0.63	-0.63	1.25*	0.25	0.50	-0.25	0.62	0.18	0.44	0.45	0.06	0.39
	Ret 13-18	0.27	-0.67	0.93**	0.01	-0.25	0.26	-0.07	-0.66	0.59	-0.07	0.30	-0.37	0.72	0.12	0.60	0.51	-0.32	0.83*
Americas (ex. U.S.)		P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1
Argentina	Ret 7-12	-2.10	-5.68	3.58*	-1.16	-2.37	1.21	-0.82	-1.34	0.53	-0.46	-1.33	0.87	-0.95	-0.89	-0.05	-0.34	-1.05	0.71
	Ret 13-18	-2.37	-3.59	1.22	-1.13	-1.19	0.06	-1.15	-1.44	0.28	-1.15	-0.82	-0.33	0.21	0.04	0.17	-0.22	-0.60	0.38
Canada #	Ret 7-12	-1.70	-4.79	3.09*	0.28	-1.60	1.87*	0.78	-0.65	1.44*	0.39	-0.23	0.62*	1.10	0.20	0.89*	0.98	0.81	0.18
	Ret 13-18	-0.98	-2.24	1.25*	-0.28	-1.41	1.12*	0.33	-0.73	1.06*	-0.09	-0.33	0.24	0.60	0.23	0.37	0.50	-0.10	0.61*
Chile ##	Ret 7-12	-1.19	-2.39	1.20	0.62	0.09	0.53	0.40	-0.39	0.79	1.46	-0.08	1.54**	0.40	-1.40	1.79	0.63	0.23	0.40
	Ret 13-18	-0.66	-2.13	1.47*	0.03	0.51	-0.49	0.33	-0.31	0.64	-0.40	-0.34	-0.07	0.82	-0.02	0.84	-0.03	0.28	-0.31
Mexico #	Ret 7-12	-0.72	-3.47	2.75*	0.21	-1.35	1.57**	0.48	-0.57	1.05	-0.05	-0.21	0.16	1.36	0.83	0.53	1.19	1.61	-0.42
	Ret 13-18	-1.12	-3.70	2.58*	-1.03	-1.56	0.53	0.23	-1.26	1.49*	-1.23	-0.45	-0.77	0.71	0.62	0.09	0.26	1.18	-0.92
Asia		P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1
Australia #	Ret 7-12	-1.44	-3.92	2.47*	0.33	-1.02	1.35*	1.22	-0.93	2.15*	0.60	-0.41	1.01*	1.31	0.20	1.11*	1.02	0.57	0.45*
	Ret 13-18	-1.80	-2.30	0.50	-0.39	-0.90	0.51	0.22	-0.69	0.91*	0.10	-0.64	0.74*	0.69	0.14	0.55*	-0.05	0.32	-0.37
China	Ret 7-12	-0.58	-1.62	1.04	-0.01	0.19	-0.20	0.39	0.25	0.14	0.81	0.67	0.13	0.18	1.33	-1.15	0.79	1.31	-0.52
	Ret 13-18	0.18	-0.01	0.19	0.68	0.53	0.16	0.06	0.76	-0.70	0.78	0.90	-0.12	0.44	0.54	-0.09	-0.51	0.57	-1.08
Hong Kong	Ret 7-12	-0.81	-2.57	1.76*	-0.20	-0.69	0.50	-0.32	-0.77	0.45	-0.06	-0.21	0.14	0.54	-0.15	0.69	0.64	0.47	0.17
	Ret 13-18	-1.12	-1.04	-0.08	-0.90	-0.80	-0.09	-0.33	-0.27	-0.06	-0.36	-0.34	-0.02	-0.14	0.19	-0.33	0.07	0.08	-0.01
India ##	Ret 7-12	-1.11	-3.98	2.87*	-1.28	-2.63	1.36	0.55	-2.06	2.61*	-0.56	-2.40	1.84*	-0.16	-0.98	0.82	0.18	-1.20	1.38**
	Ret 13-18	-2.08	-2.99	0.91	-1.79	-2.12	0.34	0.37	-1.87	2.24*	-0.30	-1.76	1.46*	-0.28	-1.54	1.27**	0.50	-0.90	1.40**
Indonesia	Ret 7-12	-3.48	-2.75	-0.73	-1.08	-1.13	0.05	-1.11	-1.04	-0.07	-0.35	-0.11	-0.24	-0.07	-0.62	0.55	-1.18	-0.71	-0.47
	Ret 13-18	-3.38	-2.50	-0.88	-2.26	-1.09	-1.17	-1.05	-0.66	-0.39	-1.67	-0.56	-1.10	-1.44	-0.44	-1.00	-0.82	0.10	-0.92
Japan	Ret 7-12	-1.04	-1.33	0.30	-0.71	-0.38	-0.33	-0.52	-0.56	0.04	-0.45	-0.13	-0.32	-0.49	-0.37	-0.13	-0.47	-0.34	-0.13
	Ret 13-18	-0.74	-1.09	0.35	-0.86	-0.92	0.07	-0.67	-0.62	-0.05	-0.57	-0.60	0.03	-0.74	-0.73	-0.01	-0.62	-0.56	-0.05
Korea	Ret 7-12	-1.86	-1.50	-0.36	-1.06	-0.76	-0.30	-0.48	-0.34	-0.14	-0.81	-0.11	-0.70	0.18	0.16	0.02	-0.49	-0.15	-0.34
	Ret 13-18	-2.16	-1.41	-0.76	-1.97	-1.01	-0.96	-0.82	-0.40	-0.42	-1.30	-0.38	-0.92	-0.61	-0.56	-0.05	-0.96	0.24	-1.20*
Malaysia	Ret 7-12	0.59	-0.66	1.24*	-0.40	-0.23	-0.17	1.15	1.08	0.07	-0.26	0.05	-0.32	0.90	0.89	0.01	0.21	0.42	-0.21
	Ret 13-18	-0.36	-0.57	0.22	-0.10	-0.33	0.23	0.36	0.76	-0.40	-0.24	0.40	-0.64	0.12	0.64	-0.52	-0.36	0.49	-0.85
New Zealand #	Ret 7-12	-0.11	-2.64	2.52*	-1.98	-0.74	-1.25	1.71	-0.40	2.11*	0.45	-0.13	0.58	1.93	0.90	1.03*	1.12	0.40	0.72**
	Ret 13-18	-0.29	-1.53	1.24**	0.23	-1.69	1.92	0.09	0.46	-0.37	-0.22	0.21	-0.43	0.68	0.54	0.15	0.94	-0.11	1.05*
Pakistan	Ret 7-12	-1.62	-2.81	1.19	-1.58	-0.80	-0.78	-0.15	0.11	-0.26	0.09	-0.12	0.21	0.10	-0.46	0.56	-0.80	-0.66	-0.13
	Ret 13-18	-2.09	-3.39	1.30	-1.22	-3.12	1.90**	-1.56	-1.62	0.07	-1.08	-0.20	-0.88	-1.66	-1.10	-0.57	-2.44	-0.05	-2.39*
Philippines	Ret 7-12	-3.66	-4.69	1.03	-2.51	-3.00	0.49	-2.19	-2.54	0.35	-1.04	-1.62	0.58	-2.23	-2.21	-0.02	-0.73	-1.07	0.33
	Ret 13-18	-3.46	-5.79	2.33*	-3.29	-1.09	-2.19*	-1.99	-3.41	1.42	-1.65	-2.27	0.62	-1.58	-2.17	0.59	-1.28	-2.06	0.78
Singapore	Ret 7-12	-0.38	-1.21	0.83	0.16	-0.09	0.26	0.28	-0.18	0.46	0.13	0.20	-0.08	0.65	0.33	0.32	0.34	0.51	-0.17
	Ret 13-18	-0.32	-0.30	-0.03	-0.22	-0.62	0.40	0.25	-0.37	0.61	0.03	-0.19	0.22	-0.03	0.33	-0.36	-0.06	-0.07	0.01

Table 4.7 continued

		V3 (High)						V2						V1 (Low)					
		AB3			AB1			AB3			AB1			AB3			AB1		
Asia		P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1
Taiwan	Ret 7-12	-2.23	-1.09	-1.14	-1.48	-0.92	-0.55	-0.11	-0.21	0.10	-0.80	-0.28	-0.51	0.11	0.17	-0.06	-0.11	0.00	-0.11
	Ret 13-18	-1.02	-1.10	0.08	-1.48	-1.36	-0.12	-0.37	-0.82	0.45	-0.71	-1.06	0.35	-0.36	-0.16	-0.19	-0.57	-0.20	-0.37
Thailand	Ret 7-12	-2.63	-3.62	0.99	-2.57	-1.64	-0.93	-1.66	-1.62	-0.04	-0.54	-1.01	0.47	-0.11	-0.28	0.17	-1.57	-1.05	-0.52
	Ret 13-18	-4.30	-1.82	-2.48**	-1.68	-1.49	-0.19	-1.96	-1.16	-0.80	-2.36	-1.42	-0.94	-1.62	-1.85	0.22	-0.75	-1.52	0.77
Europe		P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1	P3	P1	P3-P1
Austria #	Ret 7-12	-1.01	-3.08	2.06*	-0.86	-1.27	0.41	-0.27	-1.02	0.75	-0.33	-0.07	-0.26	0.45	0.66	-0.21	-0.03	0.05	-0.08
	Ret 13-18	-0.35	-1.42	1.07**	-0.63	-0.48	-0.15	0.14	-1.02	1.17*	-0.82	-0.97	0.15	0.33	-1.05	1.38*	0.16	-0.61	0.77**
Belgium #	Ret 7-12	-0.45	-1.96	1.50*	0.38	-0.09	0.48	0.22	-0.40	0.62**	0.63	0.21	0.43	1.44	0.61	0.83*	0.78	0.31	0.47
	Ret 13-18	-0.28	-0.14	-0.13	0.41	-0.02	0.43	-0.14	-1.02	0.88*	0.04	-0.17	0.21	1.29	0.69	0.59	0.57	0.03	0.54
Denmark #	Ret 7-12	-0.69	-2.61	1.92*	-0.08	-0.55	0.46	1.50	-0.38	1.88*	-0.13	-0.04	-0.10	2.05	0.19	1.86*	0.90	-0.13	1.03*
	Ret 13-18	-0.69	-1.76	1.07*	-0.70	-1.03	0.33	0.14	-0.25	0.40	-0.57	-0.61	0.03	0.66	0.11	0.55	0.23	0.11	0.11
Finland ##	Ret 7-12	-1.20	-1.44	0.24	-0.35	-1.08	0.73	0.75	-0.19	0.94	-0.15	0.99	-1.14*	1.60	-0.90	2.50*	0.94	0.35	0.59
	Ret 13-18	-0.88	-0.65	-0.24	0.40	-0.55	0.95	-0.69	-1.85	1.17	-0.06	-0.07	0.01	0.82	-0.92	1.73**	0.62	0.11	0.51
France #	Ret 7-12	-1.78	-3.23	1.45*	1.37	0.59	0.78*	-0.45	-0.94	0.49	1.80	1.36	0.43	0.52	0.39	0.13	2.56	1.86	0.70
	Ret 13-18	-1.16	-2.18	1.03**	0.25	-0.66	0.91**	-0.52	-1.02	0.50	0.77	0.03	0.74	0.02	-0.29	0.31	0.78	1.86	-1.08**
Germany #	Ret 7-12	-2.14	-3.14	1.61*	-1.33	-1.84	0.51	0.25	-1.25	1.49*	-0.19	-0.35	0.16	0.69	-0.54	1.24*	0.39	-0.75	0.65
	Ret 13-18	-2.01	-2.65	1.13*	-1.60	-2.10	0.50	-0.17	-1.17	1.00*	-0.21	-0.91	0.70**	-0.13	-1.16	1.03*	0.10	-0.88	0.48
Greece	Ret 7-12	1.94	-0.10	2.04**	1.15	-0.03	1.18	2.01	1.45	0.56	1.08	0.07	1.01	1.93	1.74	0.19	2.15	1.16	1.00
	Ret 13-18	0.80	0.87	-0.07	1.11	0.61	0.50	0.76	1.54	-0.78	0.93	1.36	-0.43	1.20	2.04	-0.84	1.62	1.32	0.30
Ireland #	Ret 7-12	0.54	-2.89	3.43*	-0.56	2.41	-2.97*	2.26	1.32	0.94**	0.98	1.36	-0.38	2.30	2.01	0.29	0.79	1.54	-0.74
	Ret 13-18	0.77	-0.94	1.71*	1.49	0.39	1.10	1.55	0.94	0.61	1.21	0.44	0.76	1.76	1.01	0.74	0.74	-0.68	1.42**
Italy #	Ret 7-12	-0.59	-0.90	1.31*	-0.25	-0.61	0.36	0.82	0.25	0.58	0.20	-0.18	0.37	1.06	0.24	0.62	0.74	0.14	0.61
	Ret 13-18	-0.54	-1.23	0.69	-0.45	-0.37	-0.08	0.12	0.29	-0.17	-0.27	-0.33	0.06	0.38	-0.14	0.52	0.62	-0.02	0.65
Netherlands #	Ret 7-12	0.02	-2.27	2.29*	0.16	-1.21	1.38*	1.37	-0.08	1.44*	0.46	0.14	0.32	1.55	1.04	0.52	1.11	0.79	0.32
	Ret 13-18	-0.34	-2.24	1.89*	-0.13	-1.85	1.72*	0.56	-0.89	1.44*	0.00	-0.27	0.27	1.06	0.08	0.98*	1.05	0.58	0.47
Norway ##	Ret 7-12	-1.76	-3.48	1.72**	0.26	0.37	-0.11	0.55	-0.10	0.64	-0.38	-0.19	-0.19	2.73	0.75	0.98	1.32	-0.15	0.47
	Ret 13-18	-2.13	-1.28	-0.85	0.32	-0.50	0.82	-0.40	-1.64	1.24**	0.51	-1.48	2.00*	1.30	0.28	1.01	0.43	-0.86	0.29
Portugal #	Ret 7-12	0.65	0.14	2.51*	0.21	1.11	-0.89	0.95	-0.43	1.38**	1.13	0.62	0.50	1.83	1.16	0.67	1.03	1.36	-0.33
	Ret 13-18	0.26	-1.47	1.73**	0.22	0.11	0.10	-0.37	-0.11	-0.25	0.44	-0.16	0.60	0.10	0.23	-0.13	1.32	-0.21	0.54
Spain #	Ret 7-12	-0.97	-1.13	1.76*	-0.53	-0.70	0.17	0.55	-0.01	0.56	0.45	0.12	0.33	1.26	0.60	0.66	0.49	0.52	-0.03
	Ret 13-18	-0.58	-0.26	-0.32	-0.69	-0.69	0.01	0.90	0.12	0.77**	0.13	-0.04	0.17	0.86	0.54	0.32	0.86	0.57	0.30
Sweden #	Ret 7-12	-1.26	-2.29	2.02*	-0.38	-1.46	1.07	0.41	-0.34	0.75	0.12	0.67	-0.54	2.30	1.39	0.71	1.41	1.12	0.29
	Ret 13-18	-1.46	-1.78	0.32	0.37	-1.31	0.68	-0.48	-0.96	0.49	-0.50	-0.02	-0.48	1.45	0.83	0.63	0.86	0.66	0.20
Switzerland #	Ret 7-12	-0.62	-2.72	2.10*	0.36	-0.07	0.43	0.87	-0.10	0.97*	0.08	0.05	0.04	1.46	0.42	1.04*	0.91	0.14	0.27
	Ret 13-18	-0.44	-1.26	0.82**	-0.50	-0.58	0.09	0.04	-0.03	0.07	0.10	-0.11	0.21	0.99	-0.37	0.35	0.66	-0.19	0.26
Turkey	Ret 7-12	3.80	4.92	-1.12	2.02	3.32	-1.29	3.49	5.66	-2.17**	2.38	5.18	-2.80*	3.19	5.34	-2.15**	2.90	5.58	-2.68**
	Ret 13-18	2.50	3.50	-1.00	1.58	3.12	-1.54	2.77	3.70	-0.93	2.28	3.83	-1.55	3.60	3.44	0.16	3.32	3.89	-0.57
UK #	Ret 7-12	-0.59	-3.33	2.74*	0.36	-0.70	1.07*	0.88	-0.47	1.35*	0.14	-0.79	0.93*	0.97	-0.46	1.42*	0.32	-0.52	0.84*
	Ret 13-18	-0.37	-1.94	1.56*	0.33	-1.32	1.65*	0.58	-0.85	1.43*	0.20	-1.32	1.52*	0.83	-0.67	1.50*	0.10	-0.64	0.74*
US #	Ret 7-12	-0.78	-2.95	2.17*	0.42	-1.27	1.69*	0.13	-0.42	0.55*	1.12	-0.37	0.49*	0.82	0.67	0.16	1.16	0.29	0.17
	Ret 13-18	-1.08	-2.89	1.81*	-0.21	-1.01	0.80*	0.10	-0.47	0.57*	0.74	-0.23	0.46*	0.95	0.42	0.53*	1.26	0.50	0.36*

Overall, the findings are consistent with hypothesis 2 suggesting that under huge uncertainty, analysts report earnings forecasts and recommendations in accord with their client's desire when the actual earnings are not yet observable. As a result, analysts continue to report favourable news to winner stocks and distort/delay unfavourable news to loser stocks. In sum, the slow absorption of ambiguous information into stock price, in particular for loser stocks, reflects investors' desire rather than inability to react to the news.

4.4.8 *Uncertainty momentum strategy vs. Standard momentum strategy*

This section computes a head-to-head comparison of a strategy based on uncertainty with the standard Jegadeesh and Titman (1993) (JT henceforth) momentum strategies. As in Table 4.2 Panel A, this section calculates the standard JT momentum strategy based on the past return performance of individual stocks and take a long (short) position in the 30% of top (bottom) performing stocks. This section measures the uncertainty momentum strategy by buying the low uncertainty winner portfolio and selling the high uncertainty loser portfolio and holding the position for six months. Low uncertainty winner (LVW) reports the average monthly portfolio returns from portfolio V1 x P3 in Table 4.5. High uncertainty loser (HVL) reports the average monthly portfolio returns from portfolio V3 x P1 in Table 4.5. Table 4.8 reports, for each country, the average monthly portfolios returns for the uncertainty momentum strategy against the standard JT momentum strategy.

The findings indicate that the uncertainty momentum strategy is more profitable than the standard JT momentum strategy. 34 of 41 countries display statistically and economically significant profits for the uncertainty momentum strategy compared to 24 of 41 countries for the JT momentum strategy. More interestingly, the results show that 7 of 12 Asia countries (except Australia and New Zealand) generate significant momentum profits by uncertainty compare to 1 of 12 Asian countries for the JT momentum strategy. This indicates that, unlike previous studies, momentum strategy can be profitable in Asia using a refined strategy based on uncertainty.

Table 4.8 Standard momentum strategy vs. Uncertainty momentum strategy

The standard momentum strategy is extracted from Table 4.2 (Panel A). The uncertainty momentum strategy is extracted from Table 4.5. Low uncertainty winner (LVW) reports the average monthly portfolio returns from portfolio V1 x P3. High uncertainty loser (HVL) reports the average monthly portfolio returns from portfolio V3 x P1. The uncertainty momentum strategy involves buying the low uncertainty winner portfolio and selling the high uncertainty loser portfolio and holding the position for six months. *(**) Denotes significance at the 5(10) per cent level.

		Standard Momentum Strategy					Uncertainty momentum Strategy			
	Begin	No. Stocks	W	L	W-L	W-L (t-stat)	LVW	HVL	LVW-HVL	LVW -HVL (t-stat)
Africa										
Israel	8701	56	-0.51	1.08	-1.59	(-2.63*)	0.72	-0.90	1.62	(2.32*)
South Africa	8701	532	1.10	-0.66	1.76	(5.51*)	1.17	-1.62	2.79	(6.67*)
Americas (ex. U.S.)										
Argentina	9207	89	0.41	-0.07	0.48	(0.62)	0.47	-3.46	3.93	(5.37*)
Brazil	9207	296	4.99	5.49	-0.50	(-0.33)	0.70	1.69	-0.99	(-1.00)
Canada	8501	1015	0.58	-1.08	1.66	(5.74*)	1.42	-2.51	3.93	(14.15*)
Chile	9210	127	1.00	0.23	0.77	(1.89**)	0.49	-0.32	0.81	(1.77**)
Columbia	9406	34	0.25	-0.91	1.16	(3.11*)	0.01	-1.76	1.77	(2.66*)
Mexico	9205	135	1.34	0.21	1.13	(3.22*)	0.36	-2.43	2.79	(4.96*)
Peru	9406	56	0.70	0.78	-0.08	(-0.10)	-1.61	-4.33	2.72	(3.16*)
Asia										
Australia	8701	940	0.14	-1.08	1.22	(3.67*)	1.11	-2.10	3.21	(11.38*)
China	9304	296	1.04	0.74	0.30	(0.50)	0.53	-1.01	1.54	(1.65)
Hong Kong	8701	640	-0.89	-0.58	-0.31	(-0.65)	0.97	-1.40	2.37	(2.09*)
India	9301	489	0.48	-0.65	1.13	(1.88**)	1.03	-2.45	3.48	(4.70*)
Indonesia	9005	238	-1.14	-0.54	-0.61	(-0.97)	-0.76	-1.88	1.12	(1.45)
Japan	8701	2580	-0.79	-0.84	0.05	(0.15)	-0.41	-0.88	0.47	(2.48*)
Korea	8801	989	-1.17	-0.93	-0.24	(-0.42)	-0.02	-0.82	0.80	(1.42)
Malaysia	8701	634	0.04	0.05	-0.01	(-0.01)	0.45	-0.22	0.67	(1.25)
New Zealand	8701	157	0.58	-0.62	1.20	(4.22*)	1.24	-2.65	3.89	(9.08*)
Pakistan	9301	163	-0.81	-0.44	-0.36	(-0.70)	-1.22	-1.63	0.41	(0.41)
Philippines	8801	184	-0.40	-0.67	0.27	(0.51)	0.50	-3.21	3.71	(5.15*)
Singapore	8701	342	0.05	-0.23	0.27	(0.62)	0.66	-0.55	1.21	(2.66*)
Taiwan	8801	612	-0.78	-0.93	0.14	(0.24)	0.46	-1.53	1.99	(3.46*)
Thailand	8709	339	-0.70	-0.32	-0.38	(-0.77)	-0.18	-1.23	1.05	(1.71**)
Europe										
Austria	8701	112	0.32	-0.57	0.89	(2.78*)	0.47	-0.99	1.46	(3.39*)
Belgium	8701	144	0.76	-0.40	1.17	(4.57*)	1.37	-0.33	1.70	(5.14*)
Denmark	8701	244	0.57	-0.36	0.93	(3.58*)	1.40	-1.58	2.98	(8.27*)
Finland	8804	161	0.25	-0.55	0.80	(1.86**)	1.32	-0.19	1.51	(2.52*)
France	8701	919	0.39	-0.95	1.35	(4.16*)	1.55	-1.62	3.17	(8.00*)
Germany	8701	922	0.16	-1.64	1.80	(5.12*)	0.73	-2.03	2.76	(6.80*)
Greece	9211	262	1.36	0.51	0.84	(1.19)	1.71	-0.19	1.90	(2.47*)
Ireland	8701	82	0.47	-0.88	1.36	(4.02*)	1.25	-2.46	3.71	(7.90*)
Italy	8701	332	0.39	-0.34	0.73	(2.17*)	1.01	-1.06	2.07	(5.25*)
Netherlands	8701	295	0.51	-1.35	1.86	(5.35*)	1.43	-1.03	2.46	(6.92*)
Norway	8701	234	0.32	-0.54	0.86	(1.86**)	1.97	-0.29	2.26	(3.99*)
Portugal	9104	93	0.15	-0.59	0.74	(2.20*)	1.41	-0.94	2.35	(4.24*)
Spain	8701	175	0.46	-0.40	0.86	(2.45*)	1.03	-1.60	2.63	(5.79*)
Sweden	8701	376	0.23	-0.98	1.21	(2.49*)	2.19	-0.97	3.16	(6.10*)
Switzerland	8701	248	0.71	-0.90	1.61	(4.91*)	1.40	-0.90	2.30	(6.37*)
Turkey	9112	313	3.66	4.44	-0.78	(-0.93)	3.92	3.82	0.10	(0.09)
UK	8701	1999	0.22	-1.64	1.86	(6.14*)	0.89	-2.39	3.28	(9.01*)
US	8301	4143	0.54	-0.83	1.36	(4.92*)	1.25	-3.21	4.46	(12.76*)

Figure 4.2 Time series average of analyst dispersion between Asia and Europe

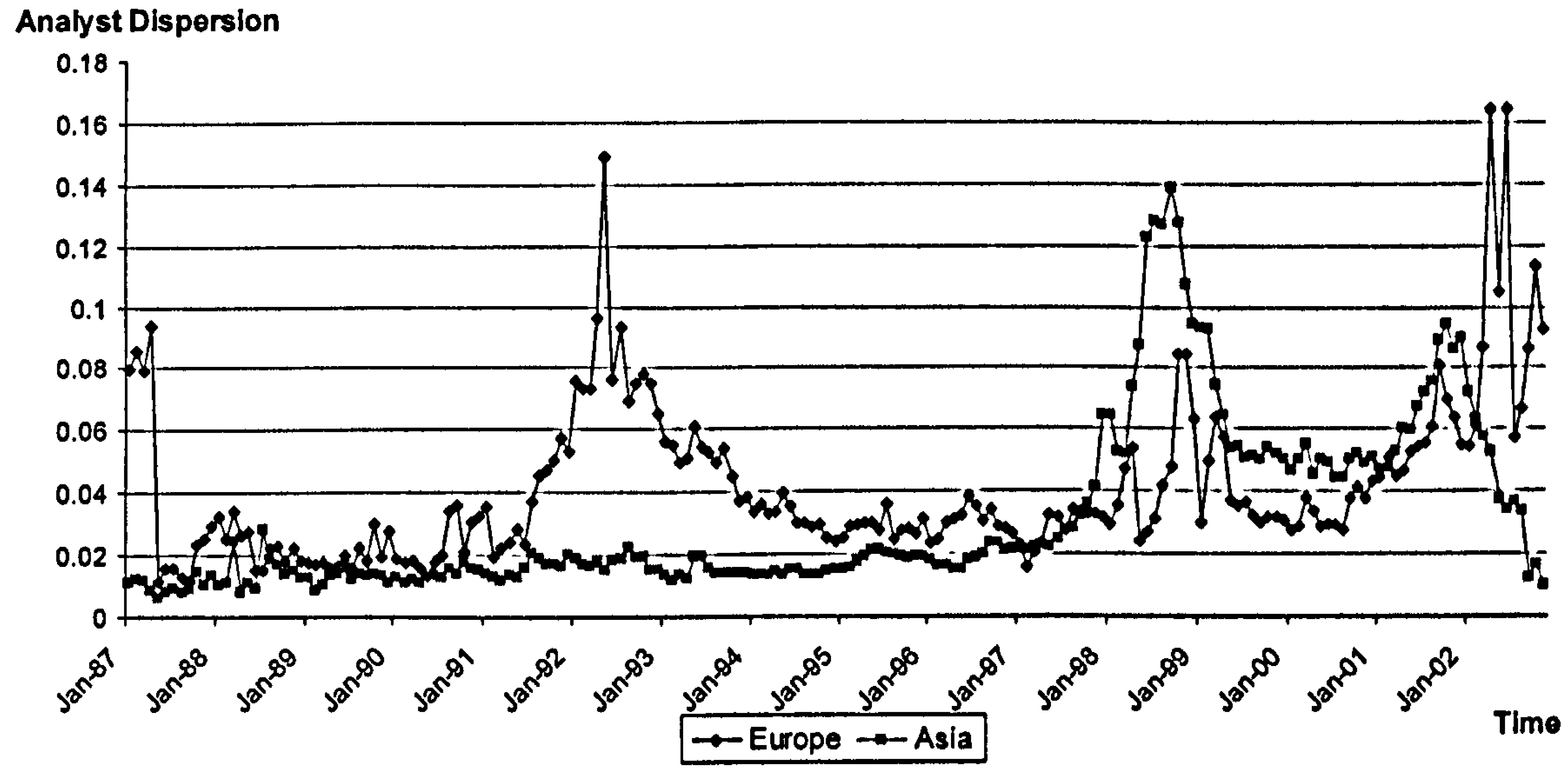
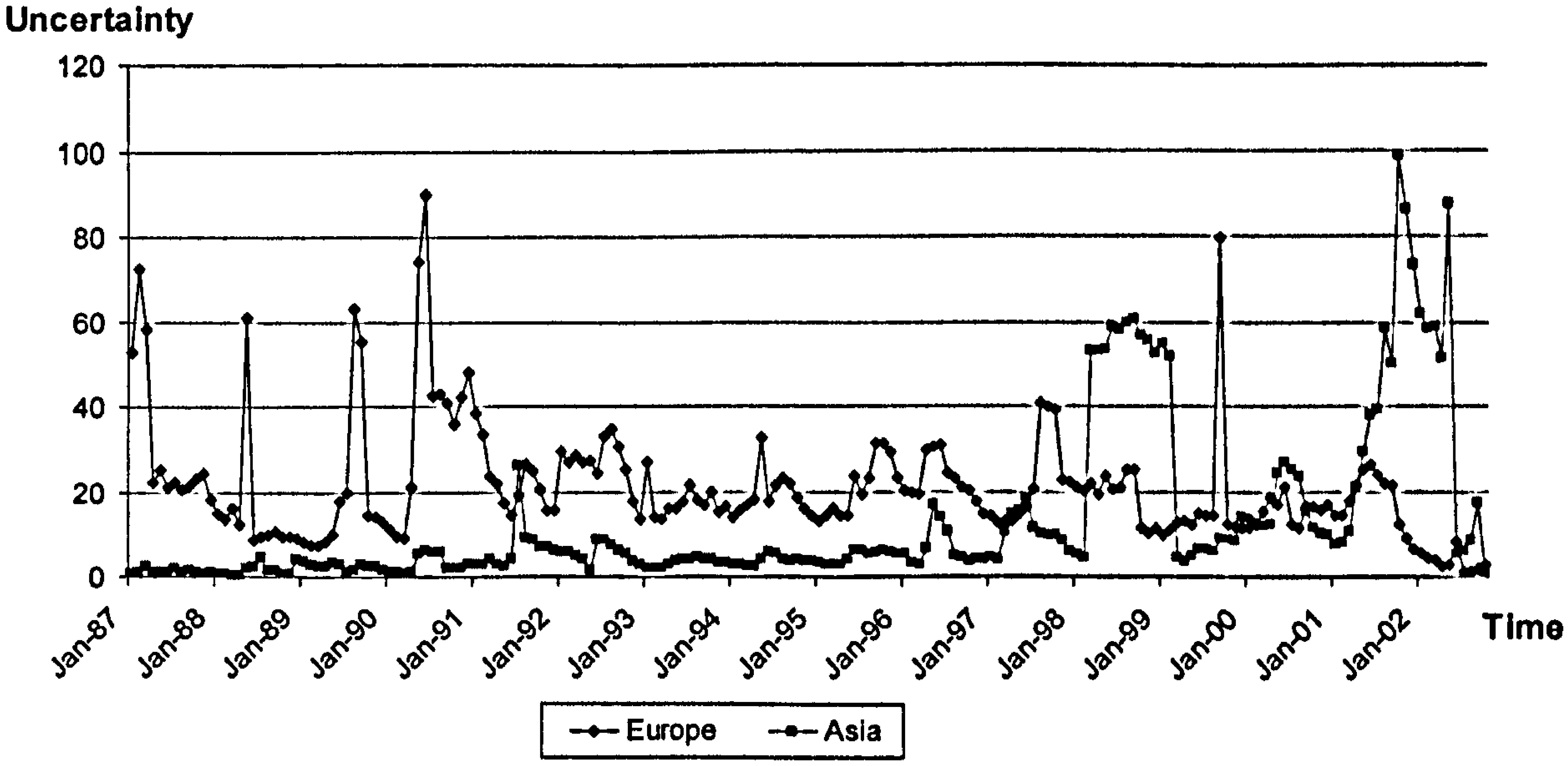


Figure 4.3 Time series average of uncertainty between Asia and Europe



Figures 4.2 and 4.3 plot the time series average of dispersion in analysts' forecast and uncertainty between Asia and Europe respectively. The figures show that both dispersion and uncertainty in Europe are higher than those in Asia. Interestingly, both dispersion and uncertainty jump up during the Asian crisis suggesting investors face hugh uncertainty towards the future prospective about the Asian economy. It is therefore not surprising to see why momentum profits are more pronounced in Europe if momentum profits have positive association with uncertainty.

4.4.9 *Crediting Rating in the US*

Avramov, Chordia, Jostova and Philipov (2007) report that the profitability of momentum strategies in the US is large and significant among high credit risk firms, but it is nonexistent among low credit risk firms. More importantly, they identify a puzzle in the disagreement between cross-sectional and time series findings. In particular, they show that momentum profits are concentrated on high credit risks firms during expansionary periods rather than recessionary, which in general should have more defaults and hence higher credit risks than expansionary periods. This section reproduces the findings of the link between momentum profits and credit rating, and examine whether analyst bias could explain the puzzle. In order to make sure that the sample of stocks is representative and comparable to Avramov, Chordia, Jostova and Philipov (2007), Panel A of Table 4.9 present the monthly returns for the loser portfolio (P1), the winner portfolio (P3), and the momentum strategy of buying the winner and selling the loser portfolio (P3 - P1) for rated and unrated firms with I/B/E/S coverage. The evidence suggests that both rated and unrated firms generate significant momentum profits. In particular, the average monthly momentum profits is 0.77 (t-stat = 3.22) for rated firms and 1.44% (t-stat = 4.70) for unrated firms.

The next step is to examine the link between momentum profits and credit risk, this section examines the average numerical credit rating for each of the three momentum portfolios over formation periods of six months. The results are reported in Panel B of Table 4.9. For each of month t, the sample is divided into the low/high credit risk group (group 1/group 3) containing the 30% best/worst rated stocks based on their S&P rating for this particular month[48].

The average profits to the P3 – P1 strategy is 0.02% (t-stat = 0.10) for the low credit risks group (rating of 10.23 ≈ BBB-) and 0.20% (t-stat = 0.97) for the medium credit risks group (rating of 12.7 ≈ BB-). The profit is much larger as well as statistically and economically significant at 1.96% (t-stat = 5.25) for the highest credit risk group (rating of 15.87 ≈ B-). In line to Avramov, Chordia, Jostova and Philipov (2007), the evidence

[48] The number of firms that is left in to each ultimate portfolio is ranging from 74 to 139 firms.

shows that momentum profits are concentrated among low-grade firms, and are nonexistent among high-grade firms. In addition, among the low rated firms, loser stocks are the dominant source of return continuation and the profitability of momentum strategies.

Table 4.9 Price Momentum, Credit Rating in the US

This table reports the average monthly portfolio returns. For each month t, all firms that are covered by I/B/E/S are included in the sample. Portfolios in Panel A are formed on all firm's six-month formation-period from *t*-7 to *t*-2: Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30% and portfolio P3 includes the best-performing 30%. The position is held for the following six month period (*t* to *t*+5). Portfolios in Panel B are formed on three credit rating groups by S&P (top 30%, middle 40%, and bottom 30%). Data on credit rating are collected from COMPUSTAT on a quarterly basis starting in 1985. The numeric S&P rating is presented in ascending order by credit risk, i.e. 1=AAA, 2=AA+, 3=AA, ..., 21=C, 22=D. For each credit rating groups, this table further sorts stocks into three portfolios based on returns from months t-7 to t-2. Portfolio P1 is an equally weighted portfolio of stocks in the worst-performing 30% and P3 is the highest 30%. The average monthly portfolios returns for winner, loser and winner minus loser portfolios are reported for each of the credit rating x analyst bias groups. The sample period is July 1985 to December 2002. *(**) Denotes significance at the 5(10) per cent level.

Panel A: Raw Momentum in Rated and Unrated Firm			
	All Firms	**Rated Firms**	**Unrated Firms**
Number of Firm	4143	1256	2887
P3 – P1	1.37 (4.93*)	0.77 (3.22*)	1.44 (4.79*)
P1	-0.83	-0.22	-1.16
P3	0.54	0.55	0.28
Panel B: Momentum and 3 Credit Rating Groups			
	Rating Group (1=Lowest Risk, 3=Highest Risk)		
	1	**2**	**3**
P3 – P1	0.02 (0.10)	0.20 (0.97)	1.96 (5.25*)
P1	0.84	0.50	-1.71
P3	0.86	0.70	0.25

As mentioned earlier the empirical evidence on the impact of credit rating on the momentum strategy suggests that momentum payoffs are concentrated among stocks with high credit risks during expansionary periods, this contradicts the fact that recessionary periods should generally have more defaults and hence high credit risks. This section proposes that the analyst bias hypothesis may offer potential explanations to the puzzle.

This section performs a three dimension analysis by first sorting stocks at the end of each month t into three portfolios based on credit risk group. This section then independently sorts stocks into three portfolios based on analyst bias. All stocks with each of the credit risk x analyst bias groups are then allocated into three portfolios based on their prior six-month returns. P1 includes the worst performing 30%, P2 includes the middle 40%, and P3 includes the best performing 30%. Panel A of Table 4.10 reports the portfolio's mean raw returns during the holding period (t to t+5). The results show that momentum profits are most concentrated with the highest credit risk x highest analyst bias group. The results are driven primarily by loser stocks. This finding indicates that the impact of credit ratings on momentum profitability is entirely explained by stocks with high analyst bias that realize lower returns.

Panel B and Panel C of Table 4.10 split the full sample in Panel A into expansionary and recessionary periods[49]. During expansions, the momentum profits are again concentrated among stocks with the highest credit risk x analyst bias group. The payoffs are statistically and economically significant 2.68% per month (t-stat = 5.34) for the poorest credit quality, highest analyst bias firms. On the other hand, during recessions, the momentum strategy payoffs in all groups are statistically insignificant[50]. The findings thus reinforce the hypothesis that analyst bias might be the reason why momentum profits are concentrated on high credit risk firms during expansionary periods.

[49] Recessionary and expansionary months are collected from NBER (www.nber.org/cycles.html)

[50] It is important to note that the results should be treated with caution since the US economy experienced long expansionary periods during the 80's and 90's. The sample for expansionary periods consists of 184 months compared to recessionary periods of 17 months.

Table 4.10 Price Momentum, Credit Rating and Analysts' Bias in the US

This table reports the average monthly portfolios returns. For each month *t*, all firms that are covered by I/B/E/S are included in the sample. Portfolios in Panel C are formed on three credit rating groups. Credit rating is calculated in the same manner as Table 4.9. For each credit rating group, stocks are further sorted into three portfolios based on analyst bias. Analyst bias is the absolute forecast error scaled by standard deviation. The average monthly portfolios returns for winner, loser and winner minus loser portfolios are reported for each of the credit rating x analyst bias groups. Recessionary and expansionary months are collected from NBER (www.nber.org/cycles.html). The sample period is July 1985 to December 2002. *(**) Denotes significance at the 5(10) per cent level.

	Analyst Bias	Rating Group (1=Lowest Risk, 3=Highest Risk)					
		1		2		3	
Overall	AB3	P3-P1=	0.01	P3-P1=	0.37	P3-P1=	2.70
			(0.06)		(1.45)		(5.45*)
		P1=	0.57	P1=	-0.03	P1=	-3.10
		P3=	0.58	P3=	0.33	P3=	-0.40
	AB2	P3-P1=	-0.02	P3-P1=	0.21	P3-P1=	0.94
			(-0.10)		(1.00)		(2.87*)
		P1=	0.81	P1=	0.51	P1=	-0.97
		P3=	0.79	P3=	0.72	P3=	-0.03
	AB1	P3-P1=	0.05	P3-P1=	0.16	P3-P1=	1.35
			(0.28)		(0.85)		(3.88*)
		P1=	1.18	P1=	1.00	P1=	-0.35
		P3=	1.23	P3=	1.16	P3=	1.00
Expansion	AB3	P3-P1=	0.12	P3-P1=	0.22	P3-P1=	2.68
			(0.60)		(0.94)		(5.34*)
		P1=	0.55	P1=	0.09	P1=	-3.00
		P3=	0.67	P3=	0.31	P3=	-0.32
	AB2	P3-P1=	0.03	P3-P1=	0.23	P3-P1=	0.82
			(0.17)		(1.18)		(2.62*)
		P1=	0.80	P1=	0.57	P1=	-0.81
		P3=	0.83	P3=	0.80	P3=	0.00
	AB1	P3-P1=	0.05	P3-P1=	0.17	P3-P1=	1.17
			(0.30)		(0.85)		(3.53*)
		P1=	1.22	P1=	1.00	P1=	-0.19
		P3=	1.27	P3=	1.17	P3=	0.98
Recession	AB3	P3-P1=	-1.12	P3-P1=	1.96	P3-P1=	2.95
			(-1.13)		(1.20)		(1.30)
		P1=	0.76	P1=	-1.36	P1=	-4.18
		P3=	-0.35	P3=	0.60	P3=	-1.23
	AB2	P3-P1=	-0.55	P3-P1=	0.00	P3-P1=	2.34
			(-0.57)		(0.00)		(1.20)
		P1=	0.89	P1=	-0.11	P1=	-2.68
		P3=	0.34	P3=	-0.11	P3=	-0.34
	AB1	P3-P1=	0.04	P3-P1=	0.06	P3-P1=	3.29
			(0.03)		(0.05)		(1.62)
		P1=	0.71	P1=	0.95	P1=	-2.09
		P3=	0.75	P3=	1.01	P3=	1.21

4.5 Conclusion

Using a sample of 22033 stocks covering 41 countries over the periods from 1983 to 2002 for the US, and from 1987 to 2002 for the rest of the world this chapter establishes a strong link between uncertainty and momentum profits across countries. In addition, the empirical findings show that greater uncertainty with greater analyst bias leads to positive returns for winner stocks and negative returns for loser stocks. As a result, the momentum effects are more likely to reflect slow absorption of ambiguous information into stock prices that could result from analysts with reputational concerns report forecasts in accord with client's beliefs rather than the true set of information. The findings provide empirical evidence for the behavioural economics theory on 'herding on the priors' and reputational effects in sender-receiver games, as well as the finance literature on the sources of momentum profits. This chapter further provides evidence based on global data that analysts' forecast dispersion reflects uncertainty rather than disagreement, consistent with Johnson (2004). The chapter suggests that the strong link between credit rating and momentum profits in the US documented by Avramov, Chordia, Jostova and Philipov (2007) could be explained by analyst bias. Finally, the chapter finds that profits from a momentum strategy based on uncertainty, by buying low uncertainty winners and selling high uncertainty losers, are superior to the Jegadeesh and Titman (1993) momentum strategy.

Overall, this chapter contribution to the behavioural economics and finance literature in twofold. First, the sources of momentum profits are more likely to have originated in an incomplete flow of information into stock prices due to analyst bias and uncertainty, leading investors to make decisions based on their priors rather than the true set of information. Second, the dispersion in analysts' forecasts that is commonly used to reflect investors' disagreement is in fact indicative of uncertainty. In addition, while risk is compensated by higher stock returns, uncertainty has the opposite effect.

The findings of this chapter have important policy implications to policy makers and financial market. In particular, the results of analyst bias, which is the tendency that analysts report earnings forecasts and recommendations in favour with client's desire rather than reflecting the true set of information, could have a negative impact to financial market and investors. Such biased opinion, however, are hard to detect or determine. In addition, the deviation of stock prices to reflect the true information could result to a less efficient market. Nevertheless, policy makers should help investors to raise enough caution to all the public information during their investment decision making.

5. Conclusion

A momentum trading strategy, buying stocks which have exhibited high returns over the previous 3 to 12 months and selling stocks with poor performance over the same period of time can generate significant abnormal returns. A plethora of explanations have been put forward for this in the past decade, both risk-based and behavioural-based. This topic is very important since it touches central themes of modern financial economics; specifically the efficient market hypothesis and asset pricing model. This thesis has aimed 1) to search for risk factors to explain momentum payoffs, 2) to examine the link between limits to arbitrage and momentum profits, also to investigate whether momentum profits are exploitable, 3) to propose another behavioural explanation based on analyst bias to explain momentum profits on a global basis.

Chapter 2 investigates whether the apparent profitability of momentum trading can be explained by business cycle variables and behavioural characteristics in three major European markets namely France, Germany and the UK. The results show evidence of price momentum in all three countries. However, possibly due to some limitations inherent in the model, the predictive regression framework of Chordia and Shivakumar (2002) based on business cycle variables cannot capture momentum profits in these markets. The conditional asset pricing model of Avramov and Chordia (2006), that allows factor loadings to vary with firm specific variables, overcomes some of the limitations of the predictive regression model of Chordia and Shivakumar (2002). Therefore, this chapter also applied the Avramov and Chordia (2006) model to the European markets investigated. In line with the findings of Avramov and Chordia (2006), the chapter shows that momentum profits in Europe are largely attributable to asset mispricing that varies systematically with global business conditions. This confirms that the idiosyncratic component of stock returns does not play any prominent role in explaining momentum profits in European markets, but business cycle variables may offer a better explanation.

Inspired by recent developments in the behavioural finance literature, especially by the ongoing debate on the role of investors' behaviour on price momentum, the Avramov and Chordia (2006) model was extended to incorporate behavioural variables. The results display a mixed role for behavioural variables across the countries, illustrating that investors' behaviour is less likely to be correlated to the business cycle and is unlikely to explain momentum profits. Moreover, the inclusion of behavioural variables does not affect the notion that momentum patterns are risk-based. This confirms that the findings of Avramov and Chordia (2006) hold for the major European financial markets and their model is robust to the inclusion of behavioural variables. Thus, the profitability of momentum strategies in Europe could be explained by risk factors, which are undetected thus far and are largely attributable to the business cycle. Overall, the finding of this chapter suggests that the apparent momentum profits are really just a premium that compensates for time-varying risk that could systematically link to business cycles or external shocks. This chapter contributes to the literature by providing evidence on the potential risk-based explanation to the momentum anomaly.

Chapter 3 examines whether stocks characterised with limits to arbitrage and high divergence in investors' beliefs contribute to momentum profits. This chapter finds that momentum profits come from loser stocks. There is strong evidence of a positive relationship between short-sale constraints and the magnitude of momentum profits. The known risk factors cannot explain the momentum profits. However, the results are inconsistent with Miller's (1977) view that stocks that are subject to both short-sale constraints and high divergence in opinion are initially overvalued and generate low subsequent returns. This chapter finds that momentum profits are linked with short sale constraints but not with divergence in opinion. On the other hand, the excessive optimism together with self attribution bias leading to overvaluation and therefore low subsequent returns explains the momentum profits.

The findings of this chapter have several implications. First, momentum profits are not exploitable as these are generated primarily by loser stocks that are costly or impossible to sell short. Second, the investors' inability to short-sell loser stocks defeats the original theme of momentum trading that argues for a self-financing hedge portfolio. Third, the persistence of momentum profits is caused by limits to arbitrage rather than by investors under-reacting to firm-specific information. Finally, the results support the view that momentum profit results primarily from mispricing due to limits to arbitrage and overconfidence; divergence in opinion does not play a role in overvaluation. This primary contribution of this chapter is that the risks and the costs involved in implementing the momentum strategy must be high, prices therefore move away from the fundamental values and limits to arbitrage.

Chapter 4 establishes a strong link between uncertainty and momentum profits across countries. In addition, the empirical findings show that greater uncertainty with greater analyst bias leads to positive returns for winner stocks and negative returns for loser stocks. As a result, the momentum effects are more likely to reflect slow absorption of ambiguous information into stock prices because analysts who are concerned for their reputations report forecasts in accordance with clients' beliefs rather than the true set of information. The findings provide empirical evidence for the behavioural economics theory on 'herding on the priors' and reputational effects in sender-receiver games, as well as the finance literature on the sources of momentum profits. This chapter further provides evidence based on global data that analysts' forecast dispersion reflects uncertainty rather than disagreement, consistent with Johnson (2004). The chapter suggests that the strong link between credit rating and momentum profits in the US documented by Avramov, Chordia, Jostova and Philipov (2007) can be explained by analyst bias. Finally, the chapter shows that profits from a momentum strategy based on uncertainty, by buying low uncertainty winners and selling high uncertainty losers, are superior to the Jegadeesh-Titman momentum strategy.

Overall, this thesis contributes to the behavioural economics and finance literature in a number of ways. First, there is a business cycle pattern within momentum profits, but whether this pattern captures any kind of risk factors remains unknown. Second, the risks and the costs involved in implementing the momentum strategy must be high, prices therefore move away from the fundamental values, and arbitragers are able to restore the price value identity. Third, the sources of momentum profits are more likely to have originated in an incomplete flow of information into stock prices due to analyst bias and uncertainty, leading investors to make decisions based on their priors rather than the true set of information. Finally, the dispersion in analysts' forecasts that is commonly used to reflect investors' disagreement is in fact indicative of uncertainty. In addition, while risk is compensated by higher stock returns, uncertainty has the opposite effect.

Nevertheless, this thesis is subject to a number of limitations on data availability and both theoretical and empirical arguments. As a result, one should exercise caution. In addition, based on the limitations of this thesis, there are several suggestions for further work. First, the findings of Chapter 2 show that momentum profits are linked to some kinds of risk factors with business cycle pattern. Future work could explore new risk factors with such pattern that could explain firm-level momentum, one suggestion steams from the recently proposed distress risk by Agarwal and Taffler (2008) and credit risk with uncertainty by Avramov and Hore (2008). Along this line, risk factors that are capturing part of the investor's behaviour but also with business cycle pattern could be the way forward.

Second, the thesis does not examine the direct effect of trading costs to implement momentum strategies. One exception is that findings in Chapter 3 provide evidence on limits to arbitrage in line with Lesmond et al. (2004), who suggest that the momentum profits cannot be exploited by investors as these are driven by small illiquid stocks which are costly or impossible to sell short. In addition, Taffler et al. (2004) report that profitable opportunities to arbitrage underperformance of going-concern stocks are severely limited due to high trading costs. Although the measure of trading costs, in particular, the costs of short-selling are not easily observable. The effect of the trading costs is important to the success of the profitability of momentum strategies. Further work could explore how trading costs affect the momentum profits during implementation on a global basis.

Third, Chapter 4 shows the strong relationship between momentum, analyst bias and uncertainty. Recently, Agarwal and Taffler (2008) show that distress risk factor could explain momentum profits. In addition, Avramov and Hore (2008) show that a combine of credit risk and information uncertainty could explain momentum under a risk-based explanation framework. Further work could therefore explore how analyst bias could integrate into distress risk factor and uncertainty to generate enough risk aversion to explain the momentum anomaly. Overall, the momentum anomaly remains to be one of the most interesting challenge to the modern finance theory.

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Appendix 1: Cluster Adjusted t-statistics[51]

In the presence of clustering, the observations within a given cluster may not be treated as independent, even though the clusters themselves may be considered independent. The detailed calculation of the covariance matrix allowing for clustering is given as follows, comparing it to the OLS estimator, and the White estimator.

OLS Variance Estimator:

$$V_{OLS} = s^2 (X'X)^{-1}$$

$$\text{where: } s^2 = \left(\frac{1}{N-k}\right)\sum_{i=1}^{N} e_i^2$$

Robust (White) Unclustered Variance Estimator:

$$V_{rob} = (X'X)^{-1}\left[\sum_{j=1}^{n}(e_i x_i)'(e_i x_i)\right](X'X)^{-1}$$

Robust Cluster Variance Estimator:

$$V_{cluster} = (X'X)^{-1}\left[\sum_{j=1}^{n_c} u_j' u_j\right](X'X)^{-1}$$

$$\text{where } u_j = \sum_{j_{cluster}} e_i x_i$$

In the calculations, e_i is the i^{th} residual and x_i is a row vector of predictors.

The variance of the clustered estimator will be higher than the robust estimator when there is positive correlation between elements of the cluster. Positive correlation means the cluster sums have more variability than the individual elements. Negative correlation within a cluster will have the reverse effect.

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[51] Source: http://www.stata.com/support/faqs/stat

Appendix 2: Performance of momentum strategies over the business cycle

This table reports the strategy's monthly profits in the holding periods. The classifications of the expansionary and contractionary periods are obtained from the Economic Cycle Research Institute (ECRI). This table also shows the average coefficients when momentum strategy payoffs (W-L) are regressed against two dummy variables indicating the state of the cycle: $R_t = \alpha_E \, Dexp_t + \alpha_E \, Drec_t + e_t$ where R_t is the momentum strategy payoffs during the holding period (t to t+5). $Dexp_t$ ($Drec_t$) is a dummy variable equal to 1 when the economy is in expansion (recession) at time t, α_E (α_E) is the average returns during an expansion (recession) and e_t is an error term. Sd refers to the standard deviations of the profits. t-statistics are adjusted for autocorrelation and heteroscedasticity and reported in parenthesis. *denotes significance at the 5% level.

	Expansionary periods			Contractionary periods		
		W – L	Sd (W-L)		W - L	Sd (W-L)
UK	01/77 – 06/79	0.93 (3.10)	1.04	07/79 – 05/81	2.26 (5.38)	1.41
	06/81 – 05/90	1.05 (2.56)	1.82	06/90 – 03/92	4.14 (7.10)	1.32
	04/92 – 12/01	2.34 (4.82)	3.19			
	α_E	1.68 (5.45)		α_C	3.37 (9.66)	
Germany	01/77 – 01/80	1.02 (2.32)	0.64	02/80 – 10/82	1.06 (3.09)	1.28
	11/82 – 01/91	1.07 (2.91)	1.72	02/91 – 04/94	0.64 (1.21)	1.55
	05/94 – 01/01	1.94 (3.58)	2.60	02/01-12/01	12.26 (7.28)	4.38
	α_E	1.41 (6.17)		α_C	2.37 (2.70)	
France	01/77 – 08/79	0.72 (0.78)	1.91	09/79 – 06/80	1.80 (2.47)	1.37
	07/80 – 04/82	0.99 (1.44)	1.84	05/82 – 12/84	1.73 (3.75)	1.32
	01/85 – 02/92	1.19 (2.09)*	2.37	03/92 – 08/93	1.92 (2.10)	2.24
	09/93 – 12/01	1.55 (3.60)	2.53			
	α_E	1.29 (4.94)		α_C	1.80 (5.63)	

Appendix 3: Descriptive statistics of business cycle variables

This table presents descriptive statistics of business cycle variables used in this chapter. YLD is measured by the rate of return on short-term financial securities. DIV is measured by dividend on value-weighted broad based market index. DEF (default risk premium) is measured as 'the yield on corporate bonds' less 'the yield long-term government bonds'. TERM (term spread) is measured as 'the yield on long-term government bonds' less 'the yield on short-term financial securities'. The sources of the data are described in Table 2.1. The sample period is January 1977 to December 2002.

		Mean	Median	St. dev.	Observations
UK	DIV	0.043	0.043	0.012	305
	YLD	0.091	0.091	0.033	305
	TERM	0.004	0.003	0.022	305
	DEF	0.010	0.010	0.004	305
Germany	DIV	0.024	0.022	0.008	305
	YLD	0.059	0.051	0.025	305
	TERM	0.008	0.012	0.013	305
	DEF	0.002	0.001	0.003	305
France	DIV	0.038	0.033	0.015	305
	YLD	0.083	0.084	0.035	305
	TERM	0.011	0.014	0.014	305
	DEF	0.003	0.003	0.005	305

Appendix 4: Summary statistics of firm characteristics

Time-series averages of equal-weighted cross-sectional means and standard deviation of the return predictors used in this chapter. Residual of institutional ownership (RIO) is the residual of equation (3.2), Firm size (S) is measured by market capitalization in millions. Divergence in opinion on each stock (Disp) is measured by the standard deviation in EPS forecasts made in 3-months prior to the formation period scaled by the stock price per share at the beginning of the month of forecast. Trading volume (VO) is measured as the ratio of the number of shares traded to the number of shares outstanding. Analyst recommendation (Rec) is measured as described in Section 3.3.5. Analyst forecast revisions (Fred) is measured as described in Section 3.3.6. RET12 (momentum) is the total individual stock return over the previous 12 months. All statistics are calculated cross-sectionally each month and are then averaged across time. The sample period is January 1993 to December 2002.

	Mean	Std dev	Number of obs (average)
RIO	0.36	0.30	1500
Firm size (S)	1183.68	739.40	1504
Disp	0.02	0.08	512
VO	1010.59	306.21	1003
Rec	2.12	0.13	134
FRev	-0.11	0.12	182
Ret12	-0.70	0.18	1400

Appendix 5: Raw momentum strategy payoffs on overlapping portfolio strategies

For each month *t*, all stocks are allocated into deciles based on their returns over past *J* months ($J = 3, 6, 9, 12$). Decile portfolios are formed monthly by weighting equally all firms in that decile ranking. The subsequent holding periods begin one month after the formation period ends. The position is then held for the following *K* months ($K = 3, 6, 9, 12$). The winners (losers) portfolio refers to the decile portfolio containing stocks ranking highest (lowest) on prior returns. The winner-loser refers the arbitrage portfolio formed by buying winners and selling losers. This table reports the strategy's raw returns during the holding period. *t*-statistics (in parenthesis) are robust to *heteroscedasticity* and autocorrelation.* denotes significance at the 5% level. The sample period is January 1993 to December 2002.

	Winner (W)	Loser(L)	W-L	T-stat
3 x 3	-0.20	-2.05	1.85	3.54*
6 x 6	0.03	-2.89	2.91	5.66*
9 x 9	-0.19	-1.79	1.60	4.57*
12 x 12	-0.48	-1.31	0.83	2.56*

Appendix 6: Momentum profits, uncertainty and analyst bias (supplement to Table 4.7)

This table reports average monthly portfolio returns sorted by uncertainty (V) and analyst bias (AB) supplement to Table 4.7. Portfolio V1 is an equally weighted portfolio of stocks in the lowest 30%, V2 is the middle 40%, and V3 is the highest 30%. Portfolio AB1 is an equally weighted portfolio of stocks in the lowest 30%, AB3 is the highest 30%. P2 is the middle 40%. The momentum strategy (P3-P1) involves buying the winner portfolio (P3) and selling the loser portfolio (P1), the average monthly momentum profits over the six months holding period (Ret 7-12) and the next six months after the holding period (Ret 13-18) are reported. *(**) Denotes significance at the 5(10) per cent level.

		V3 (High)						V2						V1 (Low)					
		AB3			AB1			AB3			AB1			AB3			AB1		
Africa		P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat
South Africa *	Ret 7-12	-1.27	2.17	3.64*	0.35	0.68	1.20	0.01	1.25	2.47*	0.78	-0.25	-0.61	0.55	0.44	1.26	0.67	0.39	0.96
	Ret 13-18	-0.12	0.93	1.79**	0.22	0.26	0.46	-0.13	0.59	1.37	0.12	-0.37	-0.84	0.35	0.60	1.61	0.37	0.83	2.09*
Americas (ex. U.S.)		P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat
Argentina	Ret 7-12	-2.54	3.58	3.00*	-2.39	1.21	1.05	-1.23	0.53	0.60	-1.64	0.87	1.00	-0.39	-0.05	-0.06	-0.32	0.71	0.77
	Ret 13-18	-2.67	1.22	1.07	-1.27	0.06	0.06	-1.13	0.28	0.24	-0.74	-0.33	-0.37	-0.86	0.17	0.18	-0.57	0.38	0.37
Canada *	Ret 7-12	-2.65	3.09	6.46*	-0.93	1.87	4.73*	0.20	1.44	4.69*	0.27	0.62	2.16*	0.79	0.89	3.42*	0.77	0.18	0.75
	Ret 13-18	-1.57	1.25	2.51*	-0.56	1.12	2.48*	0.18	1.06	3.48*	-0.05	0.24	0.76	0.45	0.37	1.28	0.32	0.61	2.39*
Chile **	Ret 7-12	-1.05	1.20	1.54	-0.02	0.53	0.87	0.56	0.79	1.57	-0.06	1.54	1.86**	-0.03	1.79	1.47	-0.05	0.40	0.82
	Ret 13-18	-1.33	1.47	2.04*	0.81	-0.49	-0.76	0.79	0.64	0.94	0.14	-0.07	-0.14	-0.13	0.84	1.58	0.32	-0.31	-0.59
Mexico *	Ret 7-12	-2.89	2.75	3.02*	-0.31	1.57	1.85**	0.34	1.05	1.58	0.47	0.16	0.24	1.52	0.53	0.86	1.53	-0.42	-0.68
	Ret 13-18	-2.15	2.58	2.61*	-0.54	0.53	0.55	0.09	1.49	2.18*	-0.31	-0.77	-1.11	0.88	0.09	0.16	0.51	-0.92	-1.56
Asia		P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat
Australia *	Ret 7-12	-1.95	2.47	5.18*	-0.21	1.35	3.65*	0.23	2.15	5.11*	0.17	1.01	3.74*	0.56	1.11	4.54*	0.79	0.45	2.01*
	Ret 13-18	-0.79	0.50	0.91	-0.22	0.51	1.13	0.12	0.91	3.37*	-0.02	0.74	2.46*	0.31	0.55	2.20*	0.45	-0.37	-1.46
China	Ret 7-12	-0.98	1.04	0.94	-0.01	-0.20	-0.19	-0.46	0.14	0.14	0.93	0.13	0.14	0.41	-1.15	-1.16	1.43	-0.52	-0.55
	Ret 13-18	0.04	0.19	0.20	1.35	0.16	0.15	-0.84	-0.70	-0.73	0.57	-0.12	-0.14	0.90	-0.09	-0.08	1.02	-1.08	-1.23
Hong Kong	Ret 7-12	-1.83	1.76	2.69*	-0.32	0.50	0.84	-0.24	0.45	0.88	-0.13	0.14	0.27	0.53	0.69	1.61	0.53	0.17	0.39
	Ret 13-18	-1.33	-0.08	-0.13	-0.68	-0.09	-0.17	-0.01	-0.06	-0.12	-0.24	-0.02	-0.03	0.23	-0.33	-0.77	0.57	-0.01	0.02
India **	Ret 7-12	-2.34	2.87	3.24*	-3.49	1.36	1.46	-1.91	2.61	3.87*	-1.06	1.84	2.04*	-0.31	0.82	1.23	-0.28	1.38	1.94**
	Ret 13-18	-1.74	0.91	1.08	-2.13	0.34	0.37	-1.72	2.24	3.55*	-1.58	1.46	2.12*	-1.31	1.27	1.95**	-0.29	1.40	1.90**
Indonesia	Ret 7-12	-3.32	-0.73	-0.69	-1.27	0.05	0.06	-0.82	-0.07	0.06	-0.32	-0.24	-0.26	-0.68	0.55	0.72	-1.41	-0.47	-0.52
	Ret 13-18	-2.51	-0.88	-0.86	-1.61	-1.17	-1.18	-0.97	-0.39	-0.47	-0.83	-1.10	-1.13	0.15	-1.00	-0.96	-0.96	-0.92	-1.07
Japan	Ret 7-12	-1.09	0.30	0.70	-0.33	-0.33	-0.91	-0.46	0.04	0.11	-0.31	-0.32	-0.97	-0.35	-0.13	-0.40	-0.41	-0.13	-0.42
	Ret 13-18	-0.86	0.35	0.90	-0.51	0.07	0.18	-0.49	-0.05	-0.15	-0.46	0.03	0.10	-0.56	-0.01	-0.03	-0.49	-0.05	-0.17
Korea	Ret 7-12	-1.36	-0.36	-0.50	-1.13	-0.30	-0.47	-0.17	-0.14	-0.25	-0.19	-0.70	-1.23	0.63	0.02	0.04	-0.27	-0.34	-0.64
	Ret 13-18	-1.29	-0.76	-1.11	-1.41	-0.96	-1.38	-0.51	-0.42	-0.70	-0.52	-0.92	-1.54	-0.02	-0.05	-0.09	-0.20	-1.20	-2.03*
Malaysia	Ret 7-12	0.16	1.24	2.11*	-0.18	-0.17	-0.26	0.91	0.07	0.12	0.21	-0.32	-0.58	0.88	0.01	0.03	0.25	-0.21	-0.41
	Ret 13-18	-0.03	0.22	0.34	-0.20	0.23	0.37	0.69	-0.40	-0.80	0.23	-0.64	-1.21	0.42	-0.52	-1.01	0.14	-0.85	-1.63
New Zealand *	Ret 7-12	-2.20	2.52	3.24*	-1.47	-1.25	-1.63	0.22	2.11	4.73*	-0.13	0.58	1.36	0.82	1.03	2.41*	1.00	0.72	1.66**
	Ret 13-18	-1.94	1.24	1.72**	-1.26	1.92	2.82*	0.45	-0.37	-0.94	-0.09	-0.43	-1.02	0.33	0.15	0.35	0.52	1.05	2.33*
Pakistan	Ret 7-12	-2.64	1.19	1.11	-1.76	-0.78	-0.66	-1.37	-0.26	-0.23	-0.88	0.21	0.25	0.01	0.56	0.65	-1.37	-0.13	-0.15
	Ret 13-18	-3.44	1.30	1.23	-3.25	1.90	1.76**	-1.13	0.07	0.08	-0.94	-0.88	-0.95	-2.78	-0.57	-0.72	-2.44	-2.39	-2.01*
Philippines	Ret 7-12	-3.96	1.03	0.89	-1.99	0.49	0.50	-2.38	0.35	0.38	-1.39	0.58	0.72	-1.40	-0.02	-0.02	-1.39	0.33	0.39
	Ret 13-18	-4.61	2.33	2.05*	-2.52	-2.19	-2.03*	-2.36	1.42	1.62	-1.32	0.62	0.71	-2.25	0.59	0.64	-0.99	0.78	0.95
Singapore	Ret 7-12	-0.77	0.83	1.50	-0.47	0.26	0.46	0.47	0.46	1.53	0.17	-0.08	-0.16	0.32	0.32	0.65	0.06	-0.17	-0.36
	Ret 13-18	-0.21	-0.03	-0.05	-0.09	0.40	1.25	0.13	0.61	1.26	0.28	0.22	0.48	-0.33	-0.36	-0.79	-0.10	0.01	0.03

		V3 (High)						V2						V1 (Low)					
		AB3			AB1			AB3			AB1			AB3			AB1		
Asia		P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat
Taiwan	Ret 7-12	-1.00	-1.14	-1.51	-1.23	-0.55	-0.84	-0.38	0.10	0.20	-0.60	-0.51	-0.91	-0.12	-0.06	-0.12	-0.07	-0.11	-0.20
	Ret 13-18	-0.99	0.08	0.11	-1.20	-0.12	-0.19	-0.53	0.45	0.86	-0.51	0.35	0.62	-0.16	-0.19	-0.36	0.01	-0.37	-0.71
Thailand	Ret 7-12	-4.00	0.99	0.87	-3.22	-0.93	-0.92	-1.59	-0.04	-0.05	-1.25	0.47	0.50	-0.32	0.17	0.21	-1.06	-0.52	-0.72
	Ret 13-18	-3.17	-2.48	-1.91**	-2.12	-0.19	-0.21	-1.71	-0.80	-0.86	-0.86	-0.94	-1.08	-1.14	0.22	0.30	-1.32	0.77	1.11
Europe		P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat	P2	P3-P1	T-stat
Austria *	Ret 7-12	-1.19	2.06	2.88*	-0.86	0.41	0.76	0.10	0.75	1.18	-0.85	-0.26	-0.65	0.42	-0.21	-0.42	-0.22	-0.08	-0.18
	Ret 13-18	-0.74	1.07	1.75**	-0.39	-0.15	-0.32	-0.28	1.17	2.72*	-0.46	0.15	0.32	-0.14	1.38	3.01*	-0.07	0.77	1.86**
Belgium *	Ret 7-12	-0.56	1.50	2.89*	0.38	0.48	1.13	0.22	0.62	1.75**	0.30	0.43	1.33	0.79	0.83	2.16*	0.43	0.47	1.43
	Ret 13-18	-0.16	-0.13	-0.35	0.09	0.43	1.04	-0.42	0.88	2.13*	0.16	0.21	0.58	0.84	0.59	1.64	0.33	0.54	1.53
Denmark *	Ret 7-12	-1.85	1.92	5.46*	0.08	0.46	1.05	0.65	1.88	5.41*	-0.20	-0.10	-0.27	1.01	1.86	4.87*	0.09	1.03	3.01*
	Ret 13-18	-1.15	1.07	3.14*	-0.38	0.33	0.69	0.03	0.40	1.08	-0.24	0.03	0.09	0.26	0.55	1.23	0.10	0.11	0.34
Finland **	Ret 7-12	-0.43	0.24	0.28	-0.36	0.73	0.94	0.68	0.94	1.27	0.33	-1.14	-2.15*	1.21	2.50	2.41*	0.74	0.59	0.89
	Ret 13-18	-0.28	-0.24	-0.22	-0.13	0.95	1.24	0.92	1.17	1.11	0.06	0.01	0.02	0.20	1.73	1.96**	0.50	0.51	0.73
France *	Ret 7-12	-2.33	1.45	2.70*	1.07	0.78	2.07*	-2.96	0.49	1.27	1.83	0.43	1.14	0.46	0.13	0.40	2.00	0.70	0.83
	Ret 13-18	-1.26	1.03	1.86**	0.45	0.91	1.73**	-0.43	0.50	1.28	0.92	0.74	1.60	0.11	0.31	0.88	0.82	-1.08	-1.81**
Germany *	Ret 7-12	-2.89	1.61	3.73*	-0.93	0.51	1.53	-0.63	1.49	3.50*	-0.31	0.16	0.43	-0.12	1.24	3.15*	-0.04	0.65	0.98
	Ret 13-18	-2.31	1.13	2.04*	-1.01	0.50	0.63	-0.73	1.00	2.29*	-0.41	0.70	1.75**	-0.54	1.03	2.10*	-0.01	0.48	0.85
Greece	Ret 7-12	1.42	2.04	1.83**	0.88	1.18	1.12	1.19	0.56	0.52	1.10	1.01	1.05	1.65	0.19	0.17	1.30	1.00	0.88
	Ret 13-18	0.83	-0.07	-0.06	1.24	0.50	0.47	0.94	-0.78	-0.68	0.42	-0.43	-0.39	1.84	-0.84	-0.75	1.74	0.30	0.26
Ireland *	Ret 7-12	0.30	3.43	3.69*	1.16	-2.97	-3.84*	1.69	0.94	1.82**	1.33	-0.38	-0.76	2.23	0.29	0.54	1.25	-0.74	-1.43
	Ret 13-18	0.44	1.71	2.09*	0.75	1.10	1.55	1.57	0.61	1.18	0.89	0.76	1.16	1.57	0.74	1.18	0.29	1.42	1.82**
Italy *	Ret 7-12	-0.65	1.31	2.03*	-0.25	0.36	0.77	0.29	0.58	1.40	0.05	0.37	0.93	0.66	0.62	1.50	0.52	0.61	1.48
	Ret 13-18	-0.59	0.69	1.40	-0.39	-0.08	-0.16	0.13	-0.17	-0.46	-0.05	0.06	0.15	0.49	0.52	1.25	0.01	0.65	1.45
Netherlands *	Ret 7-12	-0.90	2.29	4.29*	0.22	1.38	2.32*	0.69	1.44	3.42*	0.44	0.32	0.88	1.29	0.52	1.51	1.00	0.32	1.00
	Ret 13-18	-0.92	1.89	2.83*	-0.31	1.72	2.63*	0.28	1.44	2.93*	-0.09	0.27	0.63	0.79	0.98	2.16*	0.92	0.47	1.35
Norway **	Ret 7-12	-1.96	1.72	1.92**	-0.39	-0.11	-0.19	-0.10	0.64	1.11	-0.01	-0.19	-0.32	1.47	0.98	1.53	0.81	0.47	0.40
	Ret 13-18	-0.89	-0.85	-1.03	-0.52	0.82	1.00	-0.57	1.24	1.77**	0.05	2.00	2.50*	0.91	1.01	1.24	0.43	0.29	0.25
Portugal *	Ret 7-12	0.88	2.51	2.55*	0.21	-0.89	-1.26	1.12	1.38	1.68**	1.37	0.50	0.66	1.56	0.67	1.14	1.24	-0.33	-0.56
	Ret 13-18	-0.19	1.73	1.96**	0.30	0.10	0.17	0.51	-0.25	-0.27	-0.12	0.60	0.96	0.89	-0.13	-0.21	0.42	0.54	0.68
Spain *	Ret 7-12	-1.26	1.76	2.27*	-0.65	0.17	0.32	0.27	0.56	1.50	0.47	0.33	0.73	0.67	0.66	1.56	0.60	-0.03	-0.05
	Ret 13-18	-0.96	-0.32	-0.47	-0.26	0.01	0.01	0.24	0.77	1.85**	0.23	0.17	0.35	0.42	0.32	0.83	0.29	0.30	0.66
Sweden *	Ret 7-12	-1.75	2.02	2.17*	-0.69	1.07	1.51	-0.05	0.75	1.29	0.50	-0.54	-0.89	1.77	0.71	1.54	1.01	0.29	0.28
	Ret 13-18	-0.92	0.32	0.40	-0.38	0.68	0.96	-0.49	0.49	0.75	0.26	-0.48	-0.88	1.19	0.63	1.18	0.66	0.20	0.39
Switzerland *	Ret 7-12	-1.25	2.10	3.83*	-0.16	0.43	1.21	0.09	0.97	2.47*	0.08	0.04	0.10	0.62	1.04	2.79*	0.15	0.27	0.35
	Ret 13-18	-1.04	0.82	1.71**	-0.03	0.09	0.24	0.01	0.07	0.16	0.05	0.21	0.58	0.46	0.35	1.43	0.28	0.26	1.20
Turkey	Ret 7-12	4.04	-1.12	-0.93	3.93	-1.29	-1.19	4.97	-2.17	-1.77**	3.93	-2.80	-2.65*	5.07	-2.15	-1.96**	4.76	-2.68	-2.53**
	Ret 13-18	3.13	-1.00	-0.89	3.26	-1.54	-1.34	3.42	-0.93	-0.90	3.39	-1.55	-1.49	3.97	0.16	0.15	4.19	-0.57	-0.57
UK *	Ret 7-12	-1.62	2.74	5.91*	-0.14	1.07	2.65*	0.22	1.35	4.67*	0.01	0.93	3.01*	0.47	1.42	3.87*	0.31	0.84	2.67*
	Ret 13-18	-0.94	1.56	3.62*	-0.76	1.65	4.12*	-0.18	1.43	4.52*	-0.02	1.52	4.29*	0.29	1.50	3.91*	-0.04	0.74	2.23*
US*	Ret 7-12	-1.02	2.17	5.33*	-0.60	1.69	5.23*	-0.65	0.55	2.46*	-0.14	0.49	2.40*	-0.29	0.16	0.93	-0.21	0.17	1.06
	Ret 13-18	-1.08	1.81	4.56*	-0.46	0.80	2.21*	-0.30	0.57	2.28*	-0.16	0.46	2.23*	0.02	0.53	2.85*	0.13	0.36	2.20*